ESSAYS ON INTEGRATION VS. SEGMENTATION OF FINANCIAL MARKETS

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ESSAYS ON INTEGRATION VS. SEGMENTATION OF FINANCIAL MARKETS

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To my parents,

who have always supported me.

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SUMMARY

Essay I: Uniform Mortgage Regulation and Distortion in Capital Allocation

The U.S. economy is significantly influenced by local features, but most federal policies are national. In this essay, I study the unintended consequences of the uniformity of the national conforming loan limit (CLL) before 2008 on bank lending in local jumbo mortgage markets. When the national CLL increased, the jumbo share of residential mortgage markets in low-income counties was significantly reduced relative to high-income counties. I find that banks responded to the exogenous national shock by significantly increasing jumbo approval rates in low-income counties. The economic magnitude is large: a county with a \$10,000 lower median income is associated with, on average, a 6 percentage-point (or 11.77%) higher jumbo loan approval rate compared to a county with a \$10,000 higher median income. The results are not driven by credit supply changes, borrower quality changes, home price anticipation, or the demand channel. Consistent with the competition mechanism in which lenders expand jumbo credit to defend market share, I also find that banks in low-income counties lower jumbo mortgage rates and later suffer from worse mortgage performance. Furthermore, smaller and less informed banks expand jumbo credit more aggressively, and, as a result, riskier borrowers receive more credit. Overall, my results highlight negative consequences of the uniformity of federal policy in mortgage markets by showing how it can lead to distorted bank lending and reduce efficiency of credit allocation across regions.

Essay II: Housing Market Integration and Economic Convergence

In this essay, I find that the increasing housing market integration in recent decades has contributed significantly to the convergence of output, income, and total employment growth across U.S. states. States with integrated housing markets also converge in their utilization of the home equity line of credit and in the prevalence of

real-estate secured loans, which suggests the collateral channel as a key transmission mechanism through which housing market integration contributes to the economic convergence. To establish causality, I identify exogenous variations in state-level house prices using real estate related foreign direct investments that are orthogonal to state economic conditions. My findings are robust to controls for banking integration and geographic proximity, and are not driven by the performance of the real estate industry or changes in local demand. I also obtain similar results at the MSA level.

Essay III: Global Diversification with Local Stocks: A Road Less Traveled

In this essay, I document a great heterogeneity in the degree of global financial integration at the firm-level and delve into its implications for international portfolio diversification. Specifically, I estimate the degree of integration for about 14,000 sample firms per year, on average, from major developed markets over the period 1995-2014, using the R-square method. The key findings are: (i) The R-square, our measure of integration, is very widely distributed across sample firms, within and across countries; (ii) The firm-level integration is significantly affected by the three attributes tested country, industry, and style; style exerts the greatest effect, followed by country and industry; (iii) 'Local' stocks that are least driven by the common global factors are significantly more effective in portfolio risk diversification than either domestic or 'global' stocks; this result holds during the recent global financial crises; (iv) Systematically identifying local stocks and holding them optimally, investors can significantly benefit from the enhanced the mean-variance efficiency within the familiar confines of developed markets. In light of the stark heterogeneity in global integration at the granular level, inferences of the diversification gains solely from stock market indices, the usual practice, are likely to understate the potential gains that world stock markets can provide.

CHAPTER I

UNIFORM MORTGAGE REGULATION AND DISTORTION IN CAPITAL ALLOCATION

1.1 Introduction

The U.S. economy is strongly influenced by local features, however, federal policy is often nationally uniform and does not reflect differences in regional economic conditions across the country.[1] Economic theory provides the insight of such uniform pricing: consumers in areas with low costs can subsidize consumers in high-cost areas. However, is the uniform feature of such policies optimal? Does it lead to distorted agency incentives and inefficient capital allocation? In this paper, I analyze the unintended consequences of the nationally uniform conforming loan limit— the maximum dollar amount of a home loan that government-sponsored enterprises (GSE) can guarantee— in the context of U.S. residential mortgage markets, through which most households' borrowing occurs. I specifically examine how bank lending can be distorted by such uniformity across regions, which leads to inefficient credit allocation.

One way the national housing finance system explicitly affects local residential mortgage borrower access to credit is through GSEs, such as the Federal National Mortgage Association ("Fannie Mae") and the Federal Home Loan Mortgage Corporation ("Freddie Mac"). They purchase mortgages directly from the loan originators, and either hold them in their portfolio or issue mortgage-backed securities (MBS) to investors, which constitutes their dominant role in fostering the development of the secondary market. Fannie Mae and Freddie Mac are restricted by law to purchasing

[1] For example, the U.S. Postal Service delivers all first-class mails to any customer at a fixed price, independent of location.

single-family mortgages with origination balances below a specific amount, known as the "conforming loan limit" (CLL) that is set annually by The Office of Federal Housing Enterprise Oversight (OFHEO). A mortgage of a size above the CLL (i.e., a *jumbo* mortgage) cannot be purchased by GSEs and thus has lower liquidity and a higher yield. Jumbo mortgages are attractive to banks, in part because of jumbo loans' higher rates, and in part because of wealthy borrowers' extraordinary credit quality and their potential to establish deeper business relationship with banks. Prior to 2008, the CLL was increased annually and was uniform across all regions throughout the U.S., except for Alaska, Hawaii, Virgin Islands, and Guam.[2] When CLL increases, the share of jumbo loans declines since some old jumbo mortgages become conforming loans under a higher CLL. However, the reduction of jumbo share is different across regions, due to regional heterogeneity of economic development and housing market structures. To interpret, the jumbo share may not be significantly reduced in high-income counties with a sufficiently large number of expensive homes, but it can be dramatically reduced in low-income counties. This regional variation in jumbo share reduction stems entirely from the nationwide uniformity of the CLL that is largely indenpendent of local lending environment and economic forces.[3] I exploit this regional variation in local jumbo markets to examine the direct effects of such spatially uniform pricing of conforming mortgage on bank lending and credit supply distortion across local jumbo markets.

I begin by examining the aggregate credit supply at the county level after the CLL increased at the beginning of 2006. As the jumbo share shrinks after the CLL

[2]Limits for Alaska, Hawaii, Virgin Islands and Guam are 50% higher. Virgin Islands was designated a high cost area in 1992 and Guam in 2001.

[3]Each year the conforming loan limits are based on the national median home prices from October to October reported by the Federal Housing Administration (FHFA), which takes account for all home prices across 3,142 counties in the U.S. Thus, the contribution of single county home prices to the national CLL change can be largely ignored, and the change in nationwide CLL is highly independent to county local economic forces.

increases, this effect is especially large in low-income areas where there are fewer expensive houses. Specifically, I focus on jumbo market segment in each county and compute the approval rates considering all banks and credit unions that receive jumbo loan application in that county.[4] I find that, following the increase in CLL, banks expand their jumbo credit supply in low-income counties by approving significantly more jumbo mortgage applications than those in high-income areas. To quantify the economic magnitude of regional variation in raised jumbo approval rates, a county with a $10,000 lower median income is associated with, on average, a 6 percentage-point (or 11.77%) higher jumbo approval rate. A back-of-the-envelope exercise implies a $12.6 billion *additional* jumbo mortgage credit supplied to lower-than-average-income counties during the 2006-2007 period.

As a higher CLL makes jumbo mortgages scarce assets and naturally leads to more intense credit market competition, I next examine whether interbank competition acts as a determinant of credit supply increase. Theory provides controversial interpretations. Banks in a concentrated market could encourage more entry in an effort to internalize the benefits of assisting the borrowers ([132]; [150]); alternatively, banks with market power may favor established borrowers over new ones, and thus lenders may have less incentive to finance newcomers in a less competitive credit market ([162]; [32]). My empirical results, in the context of jumbo market, show that the effects of reduced jumbo share on bank lending are particularly acute for counties where the credit market is competitive. This finding is consistent with the view that banks compete for a smaller pool of jumbo borrowers by extending credit supply, and thus create adverse selection problems for their competitors ([56]; [5]).

Next, by utilizing rate spread data from the Home Mortgage Disclosure Act (HMDA) dataset, I show that banks lower the interest rates of jumbo mortgages

[4]Specifically, in forming the sample of jumbo mortgage lenders I include banks regulated by the Federal Reserve, the Federal Deposit Insurance Corporation (FDIC), and the Office of the Comptroller of the Currency (OCC), thrift institutions, and credit unions.

especially in areas where the credit market competition is more intense. Moreover, a larger increase in jumbo approval rate is associated with relatively poorer loan performance. This association is economically and statistically more significant for banks that have higher exposure to jumbo loan lending. These results further lend support to the competition channel through which banks expand jumbo credit and lower loan price to defend market share.

I also take a number of steps to rule out alternative explanations of the main finding. First, I rule out the possibility that bank-specific changes can drive my results by conducting a within-bank test. Using bank-county-year level data, I add bank-year fixed effects to account for all cross-lender variations that change over time, which eliminates the time-varying bank-specific changes that can explain our results. Intuitively, this test examines whether the same bank lending to the same county behaves differently before and after the new CLL was introduced. Second, I examine whether the change in loan quality can explain the raised jumbo approval rates in low-income areas. In particular, I use two approaches: (i) Estimate the baseline regression using a subsample of borrowers with similar credit quality before and after the CLL increase, and (ii) use a difference-in-difference framework in combination with the propensity score matching methodology over the period of 2007-2008. More details will be discussed in Section 4.3.2. Overall, my results remain robust after controlling for loan quality change. Third, I rule out the possibility that the increased approval rates are driven by higher securitization rates through adding a control variable that captures the county-level securitization intensity. Fourth, I verify that neither house price expectation nor demand channel can explain my findings. Fifth, I estimate a placebo regression one year after the CLL increase and find no statistically significant effect of jumbo share reduction on bank lending. Finally, I conduct a battery of robustness checks and verify that these results are robust to a variety of estimation techniques and variable definitions.

Furthermore, I investigate the substantial heterogeneity of lenders and borrowers across differential characteristics that may be hidden under the documented significant increase of jumbo loan approval rates in low-income counties. In particular, I find that smaller and less informed lenders expand jumbo credit more aggressively by raising approval rates, and the magnitude of this effect increases with the degree of local credit market competition. These results suggest that banks acquire private information through lending in jumbo market so that they can soften price competition through creating adverse selection problems for their competitors ([94]). Small banks that are less geographically diversified and less informed banks that have information disadvantage have especially strong desire to defend market shares for fear of being left out by their competitors. Exploiting variations in borrower characteristics, I demonstrate that borrowers receive more credit if they have (i) a higher loan-to-income ratio, i.e., lower credit quality, or (ii) refinancing mortgage applications rather than home-purchasing loans.

This paper contributes to a number of existing literatures. First, it adds value to the stream of literature that studies the effects of uniform federal policies. For example, [100] examine the impacts of the uniformity of GSE mortgage rates on wealth transfer through regional redistribution and highlight a direct mechanism by which credit market can serve to insure regional shocks. [116] shows that the regional uniformity of GSE mortgage rates lead to credit rationing. In particuular, the lack of regional variation in mortgage rates leads to the credit rationing of marginal borrowers in regions with borrower-friendly laws. My paper complements these findings by highlighting a direct channel through which uniform pricing regime in mortgage market can distort bank lending and lead to inefficient credit allocation across regions.

This paper also enriches the literature on the connection between credit market competition and the strategic use of private information ([56]; [94]; [5]), entrepreneurship and the formation of new incorporations ([23]), credit standards ([156]), the market structure of nonfinancial sectors ([36]), small-firm borrowing costs ([153]), and the supply of complex mortgages ([61]). These papers show convincingly that credit supply shock and credit market competition among banks influence their lending strategies and loan terms. Different from the existing literature, my study investigates how lenders redistribute credit across regions due to a shock triggered by the spatial uniformity of federal policy.

Finally, this paper adds to the emerging literature on understanding the causes and effects of the credit expansion in mortgage markets. Related literature has focused on supply growth in mortgage credit (e.g., [136], [137]; [74]; [60]) and on mortgage credit demand ([2] [2], [3], [4]). Different from these studies, this paper contributes to the literature by highlighting a competition channel which can also drive the recent mortgage credit expansion in jumbo market segment. Furthermore, my results establish the heterogeneity in lenders' responses and suggest that banks with liquidity and information disadvantages tend to lend more aggressively and compete with their rivals to defend market shares.

This paper is organized as follows. Section 2 discusses institutional setting. Section 3 describes data and sample. Section 4 presents the main results and the economic mechanism and rules out alternative explanations. Section 5 provides evidence of heterogeneity of lenders and borrowers. Section 6 concludes.

1.2 Institutional Background and Identification Strategy

1.2.1 Jumbo mortgage market segment

Jumbo loans are especially attractive to lenders for several major reasons. First, the jumbo/nonjumbo spread, which has varied between 15 and 25 basis points over the past two decades, leads to an enhancement of lender's income.[5] Due to the role of the Federal National Mortgage Association (Fannie Mae) and the Federal Home Loan Mortgage Corporation (Freddie Mac), securitization of residential mortgages has grown rapidly since the early 1980s ([75]). Since the legislative goal of these two government sponsored entities (GSEs) is to promote access to mortgage credit for low- and moderate-income households, they operate under a special charter limiting the size of mortgages that they may purchase or securitize. Any mortgages above this size limit are called jumbo loans and cannot be purchased by the GSEs. As noted in [128], some of the increase in yields for jumbos reflects differentials in liquidity since GSEs enhance liquidity for nonjumbo loans but not jumbos.

Second, the extraordinary credit quality of wealthy borrowers makes jumbo mortgage lending continue to be a bright spot for lenders. In contrast to nonjumbo loans, lenders keep jumbos on their balance sheets, in part because of their lower liquidity and in part because they see jumbo mortgages as a safe investment to hold, versus selling them as mortgage-backed securities.

Third, anecdotal evidence suggests that lenders are driven by the incentive of building long-term connection with jumbo borrowers. Lenders can benefit from this deeper relationship with affluent consumers in various ways, and most of the time they can expand businesses other than mortgage originations. For example, lenders are willing to target jumbo borrowers and sell them other financial products and services, in an effort to expand businesses in the local market.

1.2.2 Identification strategy

This paper examines the effect of uniform jumbo mortgage limit on bank lending by employing the nationwide change of conforming loan limits (CLLs). As previously

[5] For jumbo/nonjumbo spread, see for example [6], [128], and [2].

discussed, GSEs may only purchase mortgages below the conforming loan size limit.[6] The loan size limit increases every year by the percentage change of the national average of single-family housing prices, based on a survey of major lenders by the Federal Housing Finance Board. Prior to 2008, the size limit was uniform across all counties throughout the U.S., except for high-cost areas including Alaska, Hawaii, Virgin Islands and Guam, where the limit is 50% higher. For example, the CLL for single-family homes experienced a 16% increase, the most significant increase in history, from $359,650 in 2005 to $417,000 in 2006, and this limit is constant throughout the U.S. Because the loan limit changes only as a function of national average home price, local housing market conditions have little contribution to the change.

While counties have differentials in economic development and housing market structure, the nationwide uniform CLL serves as an instrument for regional variations in local jumbo mortgage shares. Some recent studies, for example, [2] and [7] utilize the CLL as an exogenous instrument for credit access and investigate its impact on home prices and economic outcomes. Different from these studies, I focus instead on the jumbo mortgage segment and investigate credit redistribution across regions.

Figure 1 illustrates the effects of CLL change as the identification strategy. High-income areas have relatively more expensive houses and more mortgages qualified as jumbos, but low-income areas have much fewer jumbo loans. When the CLL increased from $359,650 to $417,000 in 2006, a proportion of loans that were jumbo loans above the old 2005 CLL became conforming loans in 2006 (the blue parts), and the new

[6] The GSE guidelines that identify a mortgage loan that conforms to GSEs include not only loan size, but also borrower's loan-to-value ratio, debt-to-income ratio, credit score and history, documentation requirements, etc. Although GSEs may only purchase some of the mortgages below the conforming size limit, none of the jumbo loans can be sold to GSEs. As a result, in this paper the analysis focusing on jumbo market segment is not affected by the conforming loan criteria despite of the size limit.

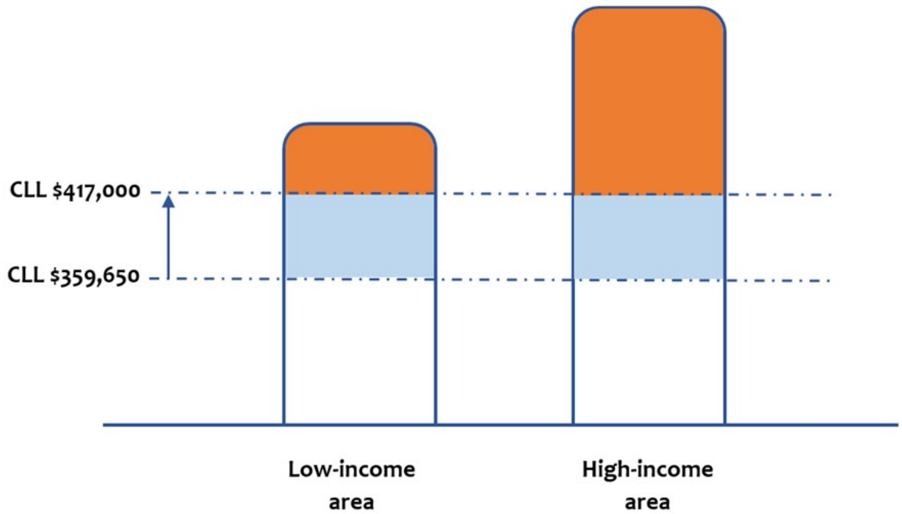


Figure 1: The effects of the change in conforming loan limit: low-income vs. high-income areas

This figure shows the effects of the change in the conforming loan limit (CLL) on low-income and high-income areas. At the beginning of 2006, the nationwide CLL increased from $359,650 to $417,000. Each bar indicates the mortgage market structure, from the smallest mortgages at the bottom to the largest ones on the top. The blue area plus the red area in each bar indicate the jumbo mortgages in the area above the old CLL. The red area in each bar indicates the jumbo mortgages in the area above the new CLL.

jumbo loan shares in the low- and high-income areas are affected differently: in low-income areas with fewer expensive homes, as the red parts show, the new jumbo share is exogenously reduced to a significantly lower level under the new CLL, while the jumbo share in high-income areas is not heavily reduced (in a relative sense) because there are more expensive homes in these areas. However, the number of lenders almost remain at a constant level right after the CLL change. This regional variation is exploited as the identification strategy to examine the effect of jumbo share reduction on bank lending strategy and credit supply, i.e., how lenders in low- and high-income areas respond differently to the increase in the uniform CLL.

1.3 Data and Sample Selection

The data of mortgage applications and originations are obtained from the Home Mortgage Disclosure Act (HMDA) dataset. The main sample covers loan applications from 2005 to 2007. All regulated financial institutions with more than $30 million in assets, such as commercial banks, credit unions, and mortgage companies, must report required data. The HMDA data include loan applications' information on the lender's identity, the location of the property, the dollar amount of the loan, application year, and whether or not the loan was accepted or sold to a third party. Borrower information is also provided, such as borrower's reported income, race, and gender.

Using HMDA data I compute the county-level and the bank-county-level approval rates (ARs) of jumbo loan applications, as a measure of credit supply to jumbo segment. The county-level AR equals the ratio of all accepted jumbo loans over all jumbo loan applications across all banks in the county, where the ratio is based on either the number or the volume of jumbo loans. The bank-county-level AR equals the ratio of jumbo loans accepted by a bank in a county over all jumbo loan applications to the bank in the county, based on either the number or the volume of jumbo loans.

To control for borrowers' credit risk in a geographical area, I include the average number of the log of the applicant's income in the county, the average loan-to-income ratio, the share of the population that is minority, and the share of female applicants in the property's county. I also include the county-level income growth rate to absorb variation in economic development and mortgage demand. The county-level income per capita and income growth rate are obtained from the Bureau of Economic Analysis. To control for the trend of the house price growth, I obtain the MSA- and state-level housing price index (HPI) from the Federal Housing Finance Agency (FHFA), then classify the counties overlapping with the MSAs and match corresponding HPI with counties. Unmatched counties are matched with the state-level

HPI.

Using lender identity, I then merge HMDA data with the bank-level data from the Reports of Condition and Income for commercial banks ("Call Reports"). I follow [128] and merge each application with the Call Report from the fourth quarter of the year prior to the mortgage application.[7] All unmatched institutions from the HMDA dataset are then matched manually using the bank's name and county name. The bank control variables include size (log of assets), leverage (the capital-asset ratio), accounting profits (net income to assets), balance-sheet liquidity (investment and traded securities to assets), share of deposit finance (ratio of deposits to total assets), deposit costs (interest expenses on deposits to total deposits), letters of credit in total assets, unused loan commitments in total assets, real estate loans in total assets, and commercial and industrial loans in total assets.

Table 1 presents the summary statistics of the merged datasets in the pre- and post-2006 periods, and for high- and low-income counties separately. I report the means and standard deviations of variable distributions at the county-year level. High- and low-income counties are splited by the median value of county income per capita in pre- and post-2006 periods separately. For high-income counties, the change in approval rates between pre- and post-2006 periods is very marginal, while the change of low-income counties is much larger. The count-(volume-) based approval rate increases from 45.6% (46.6%) in the pre-2006 period to 51.9% (53.5%) in the post-2006 period.

[7]To merge with the HMDA bank identification number, I use the Call Report identification number (RSSD ID) for banks regulated by the Federal Reserve (FR), the Federal Deposit Insurance Corporation (FDIC) certificate ID (item RSSD9050 in the Call Report) for banks regulated by the FDIC, with the Office of the Comptroller of the Currency (OCC) ID (item RSSD9055 in the Call Report) for banks regulated by the OCC, with the Office of Thrift Supervision (OTS) ID (item RSSD9037 in the Call Report) for thrift institutions regulated by the OTS, and with the National Credit Union Administration (NCUA) Charter ID (item RSSD9039 in the Call Report) for credit unions regulated by the NCUA.

Table 1: Summary statistics

This table presents summary statistics of all mortgage, bank, and socio-economic variables at the county level before and after the increase of conforming loan limit (CLL) in 2006. Mortgage application data are from HMDA loan applications and originations from 2005 to 2007. County-level socio-economic variables are based on data from the Bureau of Economic Analysis (BEA). Bank-related data are obtained from the Reports of Condition and Income for commercial banks ("Call Reports"). The CLL increased from \$359,650 in 2005 to \$417,000 in 2006. The Pre-06 period refers to the entire year of 2005, and the Post-06 period refers to two entire years of 2006 and 2007. High (low) income counties are classified as counties with higher-(lower-)than-median county-level median income in the given year. All variables are defined in Appendix A.

	High Income Counties				Low Income Counties			
	Pre-06 Limit Change		Post-06 Limit Change		Pre-06 Limit Change		Post-06 Limit Change	
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
Dependent variables								
Jumbo Acceptance Rate (Count)	0.509	0.191	0.508	0.181	0.456	0.262	0.519	0.287
Jumbo Acceptance Rate (Volume)	0.532	0.197	0.533	0.195	0.466	0.274	0.535	0.297
Jumbo Retention Rate (Count)	0.509	0.236	0.523	0.225	0.631	0.307	0.662	0.315
Jumbo Retention Rate (Volume)	0.538	0.239	0.546	0.230	0.648	0.309	0.672	0.319
Mortgage application								
No. of Loan Applications	24146	66247	23291	61251	3799	13424	3201	12008
No. of Loans Issued	10646	28816	9760	24580	1573	5734	1298	4712
No. of Jumbo Loan Applications	2672	15408	2064	12463	146	1809	96	1228
No. of Jumbo Loans Accepted	1371	7878	996	5927	73	911	44	545
No. of Jumbo Loans Retained	379	1983	287	1557	21	204	13	116
County Median Income ('000)	35.018	7.647	36.672	8.935	24.849	2.817	25.588	2.949
County Income Growth (%)	4.746	5.145	5.287	7.688	3.367	3.931	2.556	5.287
Log(Applicant Income)	4.088	0.257	4.162	0.268	3.852	0.178	3.909	0.187
Loan-to-income Ratio	2.018	0.463	2.008	0.450	1.841	0.359	1.789	0.351
Minority Applicant Fraction	0.068	0.083	0.074	0.087	0.088	0.112	0.083	0.111
Female Applicant Fraction	0.246	0.046	0.248	0.043	0.254	0.044	0.254	0.052
Bank Controls								
Log(Assets)	15.420	0.888	15.680	0.908	15.781	0.738	16.157	0.739
Leverage	0.105	0.007	0.103	0.005	0.105	0.009	0.102	0.008
Accounting Profits	0.695	0.035	0.696	0.029	0.693	0.041	0.695	0.032
Liquidity	0.168	0.033	0.165	0.027	0.163	0.041	0.159	0.035
Loans/Assets	0.695	0.035	0.696	0.029	0.692	0.042	0.694	0.034
Deposits/Assets	0.692	0.051	0.709	0.037	0.667	0.062	0.687	0.054
Deposit Cost	0.041	0.006	0.037	0.005	0.041	0.007	0.036	0.005
Letters of credit/Assets	0.001	0.000	0.001	0.000	0.001	0.000	0.001	0.000
Unused Loan Cmt/Assets	0.548	0.273	0.500	0.326	0.609	0.247	0.557	0.212
C&I Loans/Assets	0.116	0.021	0.109	0.015	0.116	0.021	0.105	0.016
Real Estate Loans/Assets	0.386	0.044	0.383	0.039	0.378	0.044	0.374	0.036
Securitization Ratio	0.685	0.091	0.662	0.081	0.620	0.113	0.597	0.108

1.4 Lender Response to Reduced Share of Jumbo Markets

1.4.1 Econometric model and main results

This section provides main results of how lenders respond to reduced jumbo shares across regions. County median home price measures the overall house price level in a county and thus can be a proxy for the extent to which the county is affected by the CLL limit change. However, if median house price is used as an explanatory variable to explain credit supply, it causes a reverse causality problem and an omitted variable problem. For example, high credit supply to local borrowers can further increase the local home prices. It is also possible that the lender and borrower's anticipation of future home prices can strengthen the association between credit supply and home price. Instead, county median income serves as a better explanatory variable in the specification. There are several reasons for the use of median income: First, as Figure 2 illustrates, county-level median income and median house price are positively correlated; second, the estimation does not suffer a reverse causality problem because credit supply in a county does not affect the contemporaneous county median income; third, other county-specific factors that affect both income and credit supply can be captured by county fixed effects.

Figure 2: Correlation of county income and county home price

This figure plots the scattered dots and the fitted line of county income and county home price. County income is the logarithm of county per capita income obtained from the Bureau of Economic Analysis (BEA). County home price is the logarithm of the median price per square foot obtained from Zillow.com. The solid line is the fitted line of the scattered dots and the shaded area is 95% confidence interval of the fitted line.

Specifically, I use aggregate county-level data and estimate

$$
\begin{aligned}
AR_{it} =& a + b_1 CountyIncome_{it} \times Post_t + b_2 CountyIncome_{it} + b_3 Post_t \\
&+ Loan\ Controls_{it} + Bank\ Controls_{it} + County\ Controls_{it} + c_i + \theta_t + \epsilon_{it}, \quad (1)
\end{aligned}
$$

where AR_{it} is the jumbo mortgage approval rate in county i in year t. Importantly, I compute AR by focusing on jumbo applications with the loan amount above $417,000 for all sample years instead of post-2006 period only. This attempt helps alleviate the concern that the pools of jumbo borrowers before and after 2006 are different.[8] Two measures of approval rates are constructed: the first one equals the fraction of approved jumbo loan applications to total jumbo loan applications made by all lenders in county i in year t, where the fraction is based on the number of jumbo loans; the second measure is similar, but the fraction is based on the volume of jumbo loans. $CountyIncome_{it}$ is the median income in county i in year t. $Post_t$ is a dummy variable equal to one for all years in or after 2006, and zero prior to that. The coefficient of interest is b_1, which measures the change in the approval rates between high-income counties and low-income counties before and after the CLL change in 2006.

In the estimation specification, I include three sets of control variables. The first set includes the following average county-level characteristics of the loan applicant pool obtained from HMDA data: the log of applicant income, the ratio of the loan size to applicant income (loan-to-income ratio), and the shares of female and minority loan applicants in the county.[9] The second set includes average bank characteristics from the Call Report: the log of bank total assets, leverage (the capital-asset ratio), accounting profits (net income to total assets), balance-sheet liquidity (investment and traded securities to total assets), share of deposit (ratio of deposits to total assets), deposit costs (interest expenses on deposits to total deposits), letters of credit in total

[8] I also estimate specifications using the strict cutoff of CLL in 2005 to define jumbo loan borrowers, i.e., loans above $359,650 are defined as jumbo loans in 2005, and find similar results.

[9] I construct county-level income and loan-to-income ratio by averaging across all of the mortgages in a county in a given year.

assets, unused loan commitments in total assets, share of real estate loans to total assets, and share of commercial and industrial loans to total assets. Third, I also control for the county-level income growth rate and the housing price index (HPI) growth rate and its lagged value. Importantly, Equation (1) includes county fixed effects (c_i) to control for any county-specific credit demand shocks and year fixed effects (θ_t) to control for time-varying factors that are constant across counties. As there may be additional autocorrelation in the residual, I cluster the standard errors by county.

Table 2: Regional variation in lender responses to uniform CLL increase

This table examines the changes in the approval rates for jumbo mortgages at the county-year level before and after the conforming loan limit increased from $359,650 to $417,000 at the beginning of 2006. The sample period is from 2005 to 2007. The dependent variables in columns 1-4 (5-8) are jumbo loan approval rates based on total number (volume) of jumbo loans at the county level. *County Income* is county per capita income obtained from the Bureau of Economic Analysis (BEA). *Log(County Income)* is the logarithm of county per capita income. The indicator variable *Post* takes the value 1 for two entire years from 2006 to 2007 and 0 for the year of 2005. *HPI Growth* is the county-level housing price index growth rate, and *HPI Growth Lag* is its lagged value. Columns 2, 4, 6, and 8 include borrower, bank, and county controls. All regression controls are defined in Appendix A. All regressions include county fixed effects and year fixed effects. Standard errors in parentheses are clustered at the county level. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.	Jumbo AR (Count)				Jumbo AR (Volume)			
County Income*Post	-0.006***	-0.004***			-0.006***	-0.005***		
	(0.001)	(0.001)			(0.001)	(0.001)		
County Income	0.013***	0.012***			0.014***	0.014***		
	(0.004)	(0.004)			(0.004)	(0.004)		
Log(County Income)*Post			-0.188***	-0.151***			-0.205***	-0.170***
			(0.024)	(0.027)			(0.025)	(0.028)
Log(County Income)			0.436***	0.453***			0.480***	0.530***
			(0.143)	(0.157)			(0.143)	(0.158)
HPI Growth		0.306***		0.299***		0.314***		0.307***
		(0.069)		(0.069)		(0.073)		(0.073)
HPI Growth Lag		0.285***		0.261***		0.287***		0.260***
		(0.082)		(0.082)		(0.086)		(0.086)
Observations	7,506	7,482	7,506	7,482	7,506	7,482	7,506	7,482
Borrower Controls		Yes		Yes		Yes		Yes
County Controls		Yes		Yes		Yes		Yes
Bank Controls		Yes		Yes		Yes		Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R2	0.138	0.156	0.140	0.157	0.136	0.161	0.139	0.162

Table 2 presents the results. The variable of interest is the interaction of $CountyIncome$ and $Post$ dummy. Column 1 shows that count-based approval rates significantly increase more in low-income counties after the CLL change at the beginning of 2006. The inclusion of county fixed effects demeans $CountyIncome$ variable. The result implies that a standard deviation decrease in county median income (7.972×\$'000) increases the jumbo approval rate, on average, by 4.78 percentage points. This effect is not trivial compared to the unconditional mean approval rate of 50.96%. Column 2 adds borrower, lender and county controls and shows that the coefficient of interest remains economically and statistically significant. Columns 3 and 4 replace county median income with its logarithm value in the estimation regressions and show that the coefficient of interest remains negative and statistically significant with a much larger magnitude. Columns 5 through 8 estimate the same baseline regression using the volume-based approval rate as the dependent variable. The coefficient of interest remains statistically significant and become slightly larger in magnitude relative to the results in columns 1 through 4. These results indicate that, after the CLL increases, jumbo loan approval rates in low-income counties are significantly larger than those in high-income counties. This finding suggests that in low-income areas where the reduction of jumbo loan share is larger, lenders tend to increase credit supply through increasing the approval rate. Figure 3 illustrates the empirical finding in Table 2. After the increase of CLL in 2006, the average jumbo approval rate in low-income counties raised by about 6.3%, from 45.6% to 51.9% which exceeds the average approval rate in high-income counties (50.8%) in post-2006 period.

1.4.2 Economic mechanism

1.4.2.1 Determinants of lender responses: competition channel

Having documented the increase in jumbo approval rate after jumbo shares decline, this subsection examines in detail the underlying economic mechanism. As the CLL change triggers a jumbo market share reduction that is exogenous to local economic

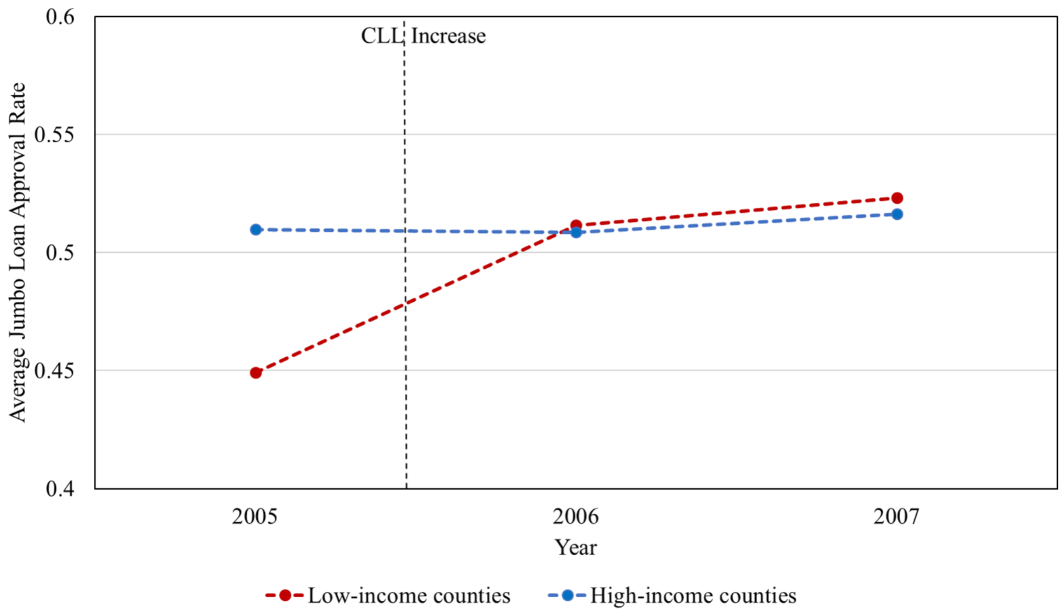


Figure 3: Average jumbo loan approval rates for low-income and high-income counties

This figure plots the average jumbo loan approval rates for low-income and high-income counties before and after the CLL increases at the beginning of 2006. Red dashed line plots the average approval rates for low-income counties. Blue dashed line plots the average approval rates for high-income counties. A county is classified as low-income (high-income) if its per capita income is below (above) the median value of all county incomes in 2005.

conditions, the credit market for jumbo mortgages becomes more competitive since lenders face a smaller pool of potential jumbo borrowers. This effect is especially stronger in low-income counties.

In the context of bank-firm relationship, theory offers competing hypotheses about how interbank competition ought to influence access to bank credit. For example, as [132] and [150] suggest, banks with market power should guarantee more entry so that they can internalize the benefits of assisting the firms at later stage if such entrants turn out to be successful. In addition to this channel, [162] and [32] show that the less competitive the conditions in the credit market, the lower the incentive for lenders to finance newcomers, because banks with market power may favor their established borrowers over new ones. In this paper I focus on the jumbo loan market in which the lending mechanism may differ from the relationship lending to the firm.

It is not certain whether jumbo mortgages work as "transaction loans" (i.e., loans that involve "arm's length" transactions), or "relationship loans". Thus, it remains as an important empirical question to examine how the competitiveness of the jumbo loan credit market affects the behavior of lenders.

This subsection empirically tests the competition channel through which the approval rate increase can be explained. I first conduct a test to examine the impact of lender competition in jumbo market by constructing a county-level local competition measure, jumbo Herfindahl-Hirschman Index (Jumbo HHI) that is defined as the sum of squared banks' market shares of jumbo loans in a given county, where the shares are based on the number of accepted jumbo loan applications.[10] One can be concerned that counties where credit markets are more competitive tend to be the ones with higher income, so the heterogeneity in the effect of reduced jumbo share captures the effect of income variation and not difference of competition. To mitigate this concern, I then conduct a test based on a subsample that includes only high-income counties. This test more directly explores the variation of competition across counties within a high-income subsample, and provides robustness of the effect of competition on credit supply increase.

Table 3 presents the results. Panel A reruns the baseline regression of Equation (1) by controling for the county-level jumbo competition measure HHI in the estimation model. The coefficient on the competition measure in column 1, -0.173, suggests that moving from fully competitive (i.e., HHI = 0) to fully concentrated (i.e., HHI = 1) would cut jumbo approval rate by 17.3 percentage points. This magnitude is substantial relative to the unconditional mean of jumbo approval rate, 50.96%. Columns 3 and 4 confirm the robustness of the coefficient on the interaction term to the use of volume-based competition measure.

[10] I also construct a similar HHI measure, where the shares are based on the volume of accepted jumbo loan applications, and obtain similar results.

Table 3: Competition channel and the increase in jumbo approval rate

This table examines how credit market competition changes the approval rates for jumbo mortgages at the county level before and after the increase of conforming loan limit at the beginning of 2006. The dataset is at the county-year level from 2005 to 2007. Panel A adds *Jumbo HHI* as a measure of jumbo lenders competition to test its relation with jumbo loan approval rates. *Jumbo HHI count (volume)* is the Herfindahl-Hirschman index (HHI) which is defined as the sum of the squared count (volume) fractions of issued jumbo loans by each lender in a given county over all issued jumbo loans in the given county. Panel B only focuses on high income counties which are above the median value of county per capita income, and the high- and low-competition counties are classified by the median *Jumbo HHI (count)* measure across the high income counties. In both panels, the dependent variables in columns 1-2 (3-4) are jumbo loan approval rates based on total number (volume) of jumbo loans at the county level. *Log(County Income)* is the logarithm of county per capita income obtained from the Bureau of Economic Analysis (BEA). The indicator variable *Post* takes the value 1 for two entire years from 2006 to 2007 and 0 for the year of 2005. All regressions control for borrower, county, and bank characteristics. Borrower controls include applicant income and loan-to-income ratio. County controls include county income growth, minority fraction, and female fraction. Bank controls include total assets, leverage, accounting profits, liquidity, deposit ratio, deposit costs, letters of credit, C&I loans, and real estate loans. All regression controls are defined in Appendix A. All regressions include county fixed effects and year fixed effects. Standard errors in parentheses are clustered at the county level. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Panel A. Competition measures of jumbo loan lenders: jumbo HHI

	(1)	(2)	(3)	(4)
Dep. Var.	Jumbo AR (Count)		Jumbo AR (Volume)	
Log(County Income)*Post	-0.159***	-0.160***	-0.184***	-0.183***
	(0.021)	(0.021)	(0.022)	(0.022)
Log(County Income)	0.431***	0.430***	0.530***	0.520***
	(0.102)	(0.103)	(0.106)	(0.107)
Jumbo HHI (Count)	-0.173***		-0.195***	
	(0.024)		(0.026)	
Jumbo HHI (Volume)		-0.149***		-0.095***
		(0.023)		(0.025)
Observations	6,562	6,562	6,562	6,562
Borrower Controls	Yes	Yes	Yes	Yes
County Controls	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adj. R2	0.335	0.330	0.320	0.302

Table 3: (Cont.) Competition channel and the increase in jumbo approval rate

Panel B. Subsample analysis: high income counties

	(1)	(2)	(3)	(4)
Dep. Var.	Jumbo AR (Count)		Jumbo AR (Volume)	
	Low Competition	High Competition	Low Competition	High Competition
Log(County Income)*Post	-0.240	-0.030***	-0.248	-0.038***
	(0.165)	(0.009)	(0.168)	(0.011)
Log(County Income)	0.912**	0.027	0.955**	0.148**
	(0.371)	(0.056)	(0.374)	(0.065)
Observations	1,553	1,816	1,553	1,816
Borrower Controls	Yes	Yes	Yes	Yes
County Controls	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adj. R2	0.177	0.638	0.173	0.586

Panel B of Table 3 presents the results based on the subsample of high-income counties. I find that, for low-competition counties in this subsample, the coefficient of the interaction term is statistically insignificant (column 1), but it turns statistically significant at the 1% level for the group of high-competition counties (column 2). The results are robust to the use of volume-based approval rate as the dependent variable (columns 3 and 4).

Overall, Table 3 provides confirmative evidence that the jumbo share effect is particularly acute for counties where the jumbo loan market is competitive. Given a same reduction of jumbo market share, lenders operating in highly competitive markets tend to raise approval rates more than lenders operating in less competitive markets. This finding is consistent with the spirit of empirical evidence in the context of bank-firm relationship, which documents that new borrowers face greater difficulty gaining access to credit in markets with concentrated lenders than in more competitive markets ([33]; [36]).

1.4.2.2 Loan pricing

If the increase in jumbo approval rate is caused by lender competition, it can be reflected in the loan pricing. Specifically, if the reduction of jumbo loan borrowers is larger in low-income areas while the number of lenders remains relatively stable, intense competition between lenders may push down the jumbo mortgage rate to defend jumbo loan market share. HMDA data provides a certain extent of mortgage-level price information that takes the form of a "rate spread". Lenders must report the spread (difference) between the annual percentage rate (APR) on a loan and the rate on Treasury securities of comparable maturity–but only for loans with spreads above designated thresholds.[11] So rate spreads are reported for some, and not all, home loans that have high rates.

Exploiting the rate spread data, I test the above hypothesis by estimating

$$\begin{aligned} RS_{it} =& a + b_1 CountyIncome_{it} \times Post_t + b_2 CountyIncome_{it} + b_3 Post_t \\ &+ Loan\ Controls_{it} + Bank\ Controls_{it} + County\ Controls_{it} + c_i + \theta_t + \epsilon_{it}, \quad (2) \end{aligned}$$

where RS_{it} is the mean or median value of jumbo mortgage rate spreads in county i in year t. $CountyIncome_{it}$ and $Post_t$ are defined as in Equation (1). c_i, θ_t are county-specific fixed effects and year fixed effects, respectively. Standard errors are clustered at the county level. If large reduction of jumbo loan borrowers in low-income areas induced high competition between lenders, one can expect to see a positive b_1, i.e., a lower mean or median value of rate spread for jumbo loans in low-income areas in the *Post* period.

Table 4 reports the results. The dependent variable in columns 1-4 (5-8) is the median (mean) value of jumbo loan rate spread in a given county in a year. Column 1 shows that the coefficient of the interaction term, 0.005, is statistically significant

[11] The thresholds vary across borrower and mortgage characteristics. See, for example, https://www.ffiec.gov/ratespread/newcalc.aspx for more information.

Table 4: Competition channel and jumbo mortgage price

This table examines the changes in the rate spread for jumbo mortgages at the county level before and after the conforming loan limit increased from $359,650 to $417,000 at the beginning of 2006. The dataset is at the county-year level from 2005 to 2007. The dependent variable in columns 1-4 (5-8) is the median (mean) value of jumbo mortgage rate spread in a county in a given year. The rate spread data is obtained from the HMDA database. *County Income* is county per capita income obtained from the Bureau of Economic Analysis (BEA). *Log(County Income)* is the logarithm of county per capita income. The indicator variable *Post* takes the value 1 for two entire years from 2006 to 2007 and 0 for the year of 2005. *HPI Growth* is the county-level housing price index growth rate, and *HPI Growth Lag* is its lagged value. Columns 2, 4, 6, and 8 include borrower, bank, and county controls. All regression controls are defined in Appendix A. All regressions include county fixed effects and year fixed effects. Standard errors in parentheses are clustered at the county level. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.	Median Jumbo Rate Spread				Mean Jumbo Rate Spread			
County Income*Post	0.005**	0.007**			0.005**	0.006**		
	(0.002)	(0.003)			(0.002)	(0.002)		
County Income	-0.001	-0.006*			0.001	-0.006**		
	(0.002)	(0.003)			(0.002)	(0.003)		
Log(County Income)*Post			0.231**	0.274**			0.247**	0.246**
			(0.110)	(0.121)			(0.105)	(0.112)
Log(County Income)			-0.032	-0.340***			0.072	-0.287**
			(0.089)	(0.126)			(0.087)	(0.119)
HPI Growth		-0.380		-0.379		-0.531*		-0.526*
		(0.297)		(0.297)		(0.290)		(0.290)
HPI Growth Lag		0.684**		0.669**		0.244		0.244
		(0.337)		(0.337)		(0.358)		(0.357)
Observations	3,713	3,689	3,713	3,689	3,713	3,689	3,713	3,689
Borrower Controls		Yes		Yes		Yes		Yes
County Controls		Yes		Yes		Yes		Yes
Bank Controls		Yes		Yes		Yes		Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R2	0.075	0.086	0.076	0.086	0.052	0.069	0.053	0.07

at the 5% level. It suggests that after the new CLL in 2006 became effective, a decrease of $10,000 median county income value is, on average, associated with a 5 basis points drop in the rate spread for jumbo mortgages. Column 2 confirms this finding by including a full set of borrower, county, and bank controls. Columns 3 and 4 test its robustness using the log value of county income and find similar results. Columns 5-8 use the mean value of jumbo loan rate spread as the dependent variable and further confirm this finding. Overall, results of Table 4 lends support to the competition channel that lenders compete for a smaller market share and lower the jumbo mortgage price for borrowers.

1.4.2.3 Proxy for loan performance

Do lenders compete more aggressively as a response to reduced jumbo loan borrowers because they simply act to defend market share or because they have better information about borrowers? the competition channel indicates that banks can simply expand their jumbo credit without carefully screening borrowers, which can result in relatively poor performance of jumbo loans. In contrast, fewer mortgages are qualified as jumbo loans after the new CLL, and thus bank's capacity constraint can be less binding and they can obtain better information about borrowers. If this is the case, banks are able to screen borrowers more carefully and price the loans more precisely. To investigate this alternative "capacity constraint" hypothesis, I test how the increase of approval rate affects mortgage performance.

I again estimate panel regressions, although I measure the data by bank-year rather than county-year. Regarding residential mortgage performance, the Call Report provides data on non-performing 1-4 family loans (NPL=1-4 family loans 90 or more days past due plus loans no longer accruing interest) and 1-4 family loans charge-offs. Specifically, I construct four measures of mortgage performance: NPL/total 1-4 family loans, NPL/total 1-4 family loans (constructed using only first liens), family loans charge-offs/total family loans, and family loans charge-offs/total loan charge-offs. In particular, the last variable captures both family loans performance and key aspects of overall lending environment. For example, when the economy is bad, family loans perform relatively poorly because bad economy pushes down bank loans in general, not because banks give out bad family loans. Thus, the last variable addresses this concern by teasing out the relative performance of family loans to overall bank loans.

Specifically, I estimate the following regression specification

$$Performance_{jt} = a + b_1 Jumbo\ AR\ Increase_{jt} + Bank\ Controls_{jt} + \zeta_j + \theta_t + \epsilon_{jt}, \tag{3}$$

where $Performance_{jt}$ is one of the four performance measures defined above for bank j at the end of year t. $JumboARIncrease_{jt}$ is the percentage change in jumbo loan approval rate for bank j from year $t-1$ to year t. b_j, θ_t are bank-specific fixed effect and year fixed effect, respectively. I cluster at the bank level for standard errors and I estimate the models over the period 2005-2008. In addition, I construct a subsample of "intensive" jumbo loan lenders, which defines "intensive" by using the fraction of a bank's issued jumbo loans over total issued family loans. In this subsample, we include only the bank-years in which the jumbo fraction is above its median value.

Table 5 reports the results. To streamline the table, I report only the coefficients on the increase of jumbo approval rates ($JumboARIncrease$). Panel A of Table 5 reports the results of the full sample. The coefficient on $JumboARIncrease$ suggests that an increase of jumbo approval rate is associated with a higher level non-performing family loans. However, the coefficients for the family loans charge-offs are not economically or statistically significant. More importantly, Panel B of Table 5 focuses on the intensive jumbo mortgages lenders and shows that the positive relation between the increase of jumbo loan approval rates and bad loan performance is stronger, both economically and statistically. For example, the coefficient in column 1 increases from 0.0004 (Panel A) to 0.0013 (Panel B). The coefficient on $JumboARIncrease$ in column 4 of Panel B increases to 0.0081 and becomes statistically significant at the 1% level. The economic magnitude is large: a 10% increase in jumbo approval rate is associated with an 8.1 basis point increase in the ratio of family loans charge-offs relative to total loan charge-offs. These results indicate that banks with larger exposure to jumbo loan lending exert stronger effect of raised jumbo approval rates on bad loans, which is consistent with the competition channel that banks compete

Table 5: Jumbo approval rate increase and loan performance

This table examines the impact of the increased approval rate of jumbo loans on bank loan performance. The dataset is at the bank-year level from 2005 to 2008. Panel A uses the full sample. Panel B uses a subsample of banks with intensive exposure to jumbo mortgage lending. This subsample includes banks with the ratio of jumbo mortgage origination volumes/total mortgage origination volumes (from the HMDA data) above its median value. In both panels, the dependent variables in columns 1, 2, 3, and 4 are *NPL/family loans* (1-4 family loans 90 or more days past due plus loans no longer accruing interest/total 1-4 family loans), *NPL/family loans only based on first liens*, *family charge-offs/family loans* (1-4 family loans charge-offs/ total 1-4 family loans), and *family charge-offs/loan charge-offs* (1-4 family loans charge-offs/ total loans charge-offs), respectively. *Jumbo AR increase* is the percentage change of the number-based approval rate in this year relative to the previous year of a bank in a given year. All columns include bank controls. All regression controls are defined in Appendix A. All regressions include bank fixed effects and year fixed effects. Standard errors in parentheses are clustered at the bank level. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Panel A. Full sample

Dep. Var.	(1) NPL/ Family loans	(2) NPL/Family loans (First lien only)	(3) Family Charge-offs/ Family loans	(4) Family Charge-offs/ Loan charge-offs
Jumbo AR increase (Volume)	0.0004**	0.0004**	0.0000	-0.0015
	(0.000)	(0.000)	(0.000)	(0.002)
Observations	9,546	9,544	9,546	8,831
Bank Controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adj. R2	0.0565	0.0449	0.0166	0.0138

Panel B. Intensive jumbo loan lenders

Dep. Var.	(1) NPL/ Family loans	(2) NPL/Family loans (First lien only)	(3) Family Charge-offs/ Family loans	(4) Family Charge-offs/ Loan charge-offs
Jumbo AR increase (Volume)	0.0013**	0.0014**	0.0002*	0.0081***
	(0.000)	(0.001)	(0.000)	(0.003)
Observations	7,012	7,010	7,012	6,362
Bank Controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adj. R2	0.0485	0.0365	0.00894	0.00765

more aggressively for market share without carefully screening borrowers.

1.4.3 Alternative explanations and robustness checks

Although the identification strategy and county fixed effects resolve several empirical concerns by exploiting the exogenous reduction of jumbo market shares, I address some remaining concerns in this section.

1.4.3.1 Lender characteristics change

The findings of increase in jumbo mortgage originations in low-income counties is consistent with the view that lenders compete for the scarce asset. However, this finding could be driven by the fact that lenders in low-income counties have different characteristics after the CLL change in 2006, such as better credit availability. To test this notion, I run a specification at the bank-county-year level and add bank-year fixed effects so that I can focus on the same bank lending to the same county before and after the new CLL, and evaluate the difference in lending. This approach also acts as a very strong robustness test for the county-level regression reported earlier because I now focus on a more homogeneous sample of lenders and can also fully account for potentially confounding factors that can impact lending decision, such as credit supply.

When conducting this within-bank test, I evaluate the CLL effect on the same bank lending to the same county. Therefore, this test removes potential biases from unobservable bank characteristics from the credit supply side. Specifically, the regression model is as follows:

$$\begin{aligned} AR_{ijt} =& a + b_1 CountyIncome_{it} \times Post_t + b_2 CountyIncome_{it} + b_3 Post_t \\ &+ Loan\ Controls_{ijt} + County\ Controls_{it} + c_i + \eta_{jt} + \theta_t + \epsilon_{ijt}, \end{aligned} \tag{4}$$

where AR_{ijt} is the jumbo mortgage approval rate by bank j in county i in year t. I compute approval rates based on jumbo loan applications in a range of \$417,000—\$600,000 for both 2005 and 2006-07 periods, so that I can compare similar borrowers in both periods. $CountyIncome_{it}$ and $Post_t$ are defined as in Equation (1). c_i is county-specific fixed effects. Importantly, I include bank-year fixed effects (η_{jt}) to control for any time-varying shocks to a bank, including credit supply change and any other factors that may affect lending decision. Standard errors are double clustered at the county and bank levels.

Table 6: Regional variation in lender responses to uniform CLL increase: within-bank tests

This table runs within-bank tests and examines the changes in the approval rates for jumbo mortgages at the county-year level before and after the conforming loan limit increased from \$359,650 to \$417,000 at the beginning of 2006. The sample period is from 2005 to 2007. The dependent variables in columns 1-4 (5-8) are jumbo loan approval rates based on total number (volume) of jumbo loans in the range of \$417,000 to \$600,000 at the bank-county level. *County Income* is county per capita income obtained from the Bureau of Economic Analysis (BEA). *Log(County Income)* is the logarithm of county per capita income. The indicator variable *Post* takes the value 1 for two entire years from 2006 to 2007 and 0 for the year of 2005. *HPI Growth* is the county-level housing price index growth rate, and *HPI Growth Lag* is its lagged value. Columns 2, 3, 4, 6, 7, and 8 include borrower, bank, and county controls. Columns 1, 3, 4, 5, 7, and 8 include county, year, and bank-year fixed effects. Columns 2 and 6 include county, year, and bank fixed effects. All regression controls are defined in Appendix A. A Standard errors in parentheses are double clustered at both the county and bank levels. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.	Jumbo AR (Count)				Jumbo AR (Volume)			
County Income*Post	-0.001**	-0.002***	-0.001**	-0.001**	-0.001***	-0.002***	-0.001**	-0.001**
	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
County Income	0.003***	0.008	0.007***	0.007	0.003***	0.008	0.007***	0.007
	(0.001)	(0.051)	(0.003)	(3.970)	(0.001)	(0.996)	(0.003)	(1.111)
HPI Growth			0.185***	0.153***			0.185***	0.153
			(0.049)	(0.023)			(0.049)	(0.319)
HPI Growth Lag			0.082*	0.096			0.079*	0.093
			(0.045)	(0.097)			(0.045)	(0.068)
Observations	235,831	49,577	50,349	48,452	235,831	49,577	50,349	48,452
Borrower Controls		Yes	Yes	Yes		Yes	Yes	Yes
County Controls		Yes	Yes	Yes		Yes	Yes	Yes
Bank Controls			Yes				Yes	
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE			Yes				Yes	
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank*Year FE	Yes	Yes		Yes	Yes	Yes		Yes
Adj. R2	0.390	0.262	0.243	0.260	0.390	0.262	0.243	0.260

Table 6 reports the results of the within-bank test. I again find that banks increase jumbo loan originations to low-income counties in the post-2006 period. After controlling for county, year, and bank-year fixed effects, the results imply that a $10,000 decrease in county median income increases the jumbo approval rate, on average, by 100 basis points after the new CLL becomes effective (columns 1 and 5), and the results remain robust after controlling for county-specific and loan characteristics (columns 2 and 6). Even after additionally controlling for house price trend, the coefficients remain statistically significant (columns 4 and 8). These results strongly support the view that lenders lend more aggressively after the jumbo share declines.

1.4.3.2 Borrower quality change

Although in approval rate calculation I focus on similar groups of jumbo borrowers with the loan amount above $417,000 for both 2005 and 2006-07, there still might be a potential concern of differential borrower quality: If the pool of jumbo borrowers in 2006 was better in quality than those in 2005, the increase of approval rate may not be a result of the reduced jumbo share but rather a reflection of better borrower quality.

I test for such concerns by comparing the approval rates for the post-2006 jumbo loan borrowers and the subset of 2005 jumbo loan borrowers that have similar characteristics with post-2006 borrowers. Specifically, I use the lowest reported applicant income and the highest loan-to-income (LTI) ratio among jumbo loan applications in 2006 as thresholds, and pick 2005 jumbo loan applicants that have higher-than-06-lowest income *AND* lower-than-06-highest LTI ratio (both adjusted for inflation rate) to form the subset of borrowers. Then I re-calculate the county-level approval rate in 2005 based on the subset of borrowers in each county in 2005. If the borrower quality concern is the case, one would expect to see a similar approval rate on the subset of 2005 jumbo loan borrowers who had similar characteristics with 2006 jumbo loan borrowers. However, the results in Table 7 show the opposite. Columns 1-4 show that the impact of reduced jumbo share on bank lending after 2006 remains significant, as the coefficient of the interaction term is statistically significant. The results are similar for the volume-based measures of approval rates (not reported).

One may still worry that the increase in jumbo mortgage origination can be a result of other borrower or lender characteristics or some county-specific factors, in addition to income and LTI ratio. To further mitigate this concern, I then exploit the effect of an event of the county-level conforming loan limit changes at the beginning of 2008. The national conforming loan limit for mortgages that finance single-family one-unit properties remained constantly at $417,000 during 2006-2007, with limits 50 percent higher for four statutorily-designated high cost areas: Alaska, Hawaii, Guam, and the U.S. Virgin Islands. Beginning in 2008, various legislative acts increased the loan limits in certain high-cost counties in the United States to reflect local price differences. More specifically, there are two sets of loan limits: "General" and "High-Cost". The "High-Cost" areas are determined by Fannie Mae's regulator, the Federal Housing Finance Agency (FHFA). The Economic Stimulus Act of 2008 temporarily increased the loan limits in high-cost areas. A total of 293 counties were determined by FHFA as high-cost areas and thus utilized various CLLs higher than $417,000 for mortgages to finance single-family one-unit properties.[12] Other counties that were not determined as high-cost areas are "General" areas. Then, the Housing and Economic Recovery Act (HERA) of 2008 permanently changed Fannie Mae's charter to expand the definition of a "conforming loan" to include "high-cost" areas on loans originated on or after January 1, 2009. As a result, for those counties determined as high-cost areas and thus had raised CLL, the potential pool of jumbo loan borrowers shrunk and the competitiveness increased given a relatively steady number of lenders in the area.

[12]The map of the high-cost areas in 2008 is shown in Figure A1.

Table 7: Alternative explanations: borrower credit and securitization ratio improvements

This table examines alternative explanations of the impacts of the CLL change on the approval rates for jumbo mortgages at the county-year level. The sample period is from 2005 to 2007. The dependent variables in columns 1-6 are jumbo loan approval rates based on total number of jumbo loans at the county level. In columns 1-4, I calculate approval rates in each county for jumbo loan applications in 2005 based on a subset of borrowers who are BOTH above the lowest income of 2006 applicants *AND* below the highest LTI ratio of 2006 applicants, with income adjusted by the inflation rate. *County Income* is county per capita income obtained from the Bureau of Economic Analysis (BEA). *Log(County Income)* is the logarithm of county per capita income. The indicator variable *Post* takes the value 1 for two entire years from 2006 to 2007 and 0 for the year of 2005. Columns 5-6 further control for county-level securitization ratio which is defined as the weighted average securitization ratio of banks in a given county (weighted by bank market shares), and for each bank the securitization ratio is computed as the total volume of securitized mortgages divided by the total volume of issued mortgages. Other regression controls are defined in Appendix A. All regressions include county fixed effects and year fixed effects. Standard errors in parentheses are clustered at the county level. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	Jumbo AR (Count)					
	Subsample_LTI_Income				Control for Sec ratio	
County Income*Post	-0.004***	-0.003***			-0.004***	
	(0.001)	(0.001)			(0.001)	
County Income	0.008*	0.006*			0.012***	
	(0.004)	(0.004)			(0.004)	
Log(County Income)*Post			-0.147***	-0.122***		-0.151***
			(0.023)	(0.026)		(0.027)
Log(County Income)			0.243	0.191		0.453***
			(0.162)	(0.149)		(0.157)
Securitization Ratio (Cty Mean)					-0.625***	-0.631***
					(0.113)	(0.112)
Observations	6,903	6,879	6,903	6,879	7,482	7,482
Borrower Controls		Yes		Yes	Yes	Yes
Bank Controls		Yes		Yes	Yes	Yes
County Controls		Yes		Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R2	0.180	0.185	0.181	0.186	0.156	0.157

To evaluate the effect of the determination of high-cost areas, I first identify control counties that are highly similar to the high-cost areas but are unaffected by this determination. Specifically, I use comprehensive information on county-level socioeconomic, borrowing, and lending characteristics to find similar control samples before the determination of high-cost areas. Second, to further establish the empirical robustness of this approach, I follow [1] and construct a synthetic control sample loan by loan, by selecting similar loans that resemble relevant observable loan characteristics. For each of the loan applications submitted in the "treated" counties, i.e., the counties that were determined as the high-cost areas, I identify a loan application most similar to it that was submitted elsewhere in the country over the year. Once a loan application is matched with one in the treated area, I remove it from the potential pool of control loan applications. The full list of variables considered for both county- and loan-level matching is summarized in Panel A of Table 8. The panel shows that for each observable characteristics the samples have very similar properties.

The basic county-level regression specification based on a classic difference-in-difference framework has the following form:

$$\begin{aligned} AR_{it} =& a + b_1 Treated_i \times Post_t + b_2 Treated_i + b_3 Post_t \\ &+ Borrower\ Controls_{it} + Bank\ Controls_{it} + County\ Controls_{it} + c_i + \theta_t + \epsilon_{it}, \end{aligned} \tag{5}$$

where AR_{it} is the approval rate in county i in year t. $Treated_i$ is a dummy variable that takes the value of one if county i is determined as a high-cost area and zero otherwise. $Post_t$ is a dummy variable equal to one for all years in or after 2008, and zero prior to that. Borrower and bank control variables listed in Panel A of Table 8 are county-level averages. The coefficient of interest is b_1, which measures the change in the approval rates between treated and control counties before and after the high-cost determination in 2008.

The results are reported in columns 1-6, Panel B of Table 8. Even with a small

Table 8: Reduction of jumbo share and approval rate increase: difference-in-difference analysis and propensity score matching

Panel A presents summary statistics of county-level and loan-level key variables as of end-2007 in matched treated (counties that are determined as "high-cost" areas by the Federal Housing Finance Agency (FHFA) in 2008 and matched with control counties based on the listed observables) and matched control (counties that are not determined as "high-cost" areas and matched with treated counties based on the listed observables) counties. Panel B reports estimates of panel regressions at the county-year level in columns 1-6, where the dependent variables are the number-(volume-)based jumbo loan approval rates in columns 1-3 (4-6). Columns 7-9 report the regressions at the loan-year level, where the dependent variable is the *Accept* dummy that takes the value of 1 if the jumbo mortgage application is accepted by the bank and 0 otherwise. The sample period is from 2007 to 2008. The indicator variable *Post* takes the value 1 for the year of 2008 and 0 for the year of 2007. In columns 1-6, *Treated* is a dummy variable that takes the value of 1 if the county is determined as a "high-cost" county in 2008 and 0 otherwise. The included control variables are listed in Panel A and defined in Appendix A. All regressions include county and year fixed effects. Standard errors in parentheses are clustered at the county level. In columns 7-9, Treated is a dummy variable that takes the value of 1 if the jumbo mortgage is submitted in a "high-cost" county that is determined in 2008 and 0 otherwise. The included control variables are listed in Panel A and defined in Appendix A. All regressions include county, bank, and year fixed effects. Standard errors in parentheses are double clustered by bank and county. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Panel A. Summary statistics for treated and control counties/mortgages

	County-level			Loan-level	
	Control Mean	Treated Mean		Control Mean	Treated Mean
Borrower Controls					
Log(Applicant Income)	4.381	4.743	Log(Applicant Income)	5.650	5.327
LTI Ratio	2.910	2.849	LTI Ratio	3.760	3.442
Minority Fraction	0.141	0.148	Minority Dummy	0.129	0.192
Female Fraction	0.270	0.270	Female Dummy	0.174	0.224
Lender Controls					
Log(Assets)	16.171	15.509	Log(Assets)	19.777	19.058
Leverage	0.108	0.109	Leverage	0.091	0.092
Accounting Profits	0.691	0.685	Accounting Profits	0.514	0.610
Liquidity	0.152	0.164	Liquidity	0.124	0.150
Loans/Assets	0.691	0.685	Loans/Assets	0.514	0.610
Deposits/Assets	0.687	0.705	Deposits/Assets	0.626	0.674
Deposit Cost	0.035	0.038	Deposit Cost	0.037	0.035
Letters of credit/Assets	0.001	0.001	Letters of credit/Assets	0.003	0.002
Unused Loan Cmt/Assets	0.429	0.418	Unused Loan Cmt/Assets	0.378	0.499
C&I Loans/Assets	0.114	0.110	C&I Loans/Assets	0.096	0.112
Real Estate Loans/Assets	0.363	0.385	Real Estate Loans/Assets	0.244	0.307
Securitization Ratio	0.658	0.636	Securitization Ratio	0.642	0.581
			BHC Dummy	0.996	0.937
County Controls					
County Income Mean ('000)	38.365	54.282	County Income Mean ('000)	40.306	49.010
County Income Growth (%)	4.705	4.616	County Income Growth (%)	3.768	4.240
No. of matched units	20	76	No. of matched units	7,334	305,993

Table 8: (Cont.) Reduction of jumbo share and approval rate increase: difference-in-difference analysis and propensity score matching

Panel B. High cost areas and jumbo mortgage approval rates

	County-level						Loan-level		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dep. Var.	Jumbo AR (Count)			Jumbo AR (Volume)			Accept		
Treated*Post	0.076**	0.087**	0.129**	0.106***	0.123**	0.282**	0.045**	0.041**	0.024**
	(0.028)	(0.036)	(0.055)	(0.027)	(0.053)	(0.108)	(0.020)	(0.019)	(0.012)
Observations	154	154	154	154	154	154	383,925	383,925	383,925
Borrower Controls		Yes	Yes		Yes	Yes		Yes	Yes
Bank Controls			Yes			Yes			Yes
County Controls			Yes			Yes			Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE							Yes	Yes	Yes
Adj. R2	0.219	0.251	0.225	0.260	0.277	0.344	0.111	0.112	0.113

matched sample comprising 154 county-year observations, the coefficient of the interaction term is still significant at the 5% level, and it is robust to the inclusion of various control variables and county and year fixed effects. This finding shows that after the high-cost area determination, the treated counties that had a reduced pool of jumbo loan borrowers experienced an increased jumbo credit supply.

Then I estimate loan-level regressions on a matched sample of loan applications. Particularly, the specification has the following form:

$$\begin{aligned} Accepted_{ijt} =& a + b_1 Treated_i \times Post_t + b_2 Treated_i + b_3 Post_t \\ &+ Borrower\ Controls_{ijt} + Bank\ Controls_{ijt} + County\ Controls_{it} \\ &+ c_i + \theta_t + \gamma_{Bank} + \epsilon_{ijt}, \end{aligned} \tag{6}$$

where subscripts i, j, and t denote counties, loan applications, and years, respectively. $Accept_{ijt}$ is a dummy variable that takes the value of one if the application is accepted and zero otherwise. $Treated_i$ is a dummy variable that takes the value of one if the application is submitted in county i that is determined as a high-cost area, and zero otherwise. Borrower- and bank-specific controls are based on each loan application.

I also control for county, year, and bank fixed effects.

Columns 7-9, Panel B of Table 8 report the loan-level regression results. The coefficients of the interaction term are positive and highly significant, which implies that the loan application in the treated counties after the determination in 2008 is more likely to be accepted. Overall, the results are consistent with the findings in Table 2, which suggests that our results are not driven by potential changes in loan quality.

1.4.3.3 Securitization rate

Could the increase in jumbo mortgage approval rate be driven by the enhanced bank liquidity due to high securitization rate? This is possible if the majority of accepted loans below CLL are conforming loans, and banks sell conforming loans due to the secondary market activities of the GSEs which further increases banks' balance sheet liquidity. Even after the within-bank tests and the results with bank-year fixed effects, I still conduct an additional test to address this concern.

I include a county-level aggregate securitization rate as an additional control variable that proxy for the average banks' balance sheet liquidity in each of the counties. Specifically, in each year I calculate the securitization ratio of the number of securitized mortgages over total number of accepted mortgages for each bank, then in each of the counties I calculate the weighted securitization ratio considering all the banks that are operated in the county, where the weight is defined as number of mortgages issued by each bank in a given county over the total issued mortgages in that county.[13] This variable controls for the regional variation in average banks' balance sheet liquidity at the county level.

[13]To precisely capture the effect of CLL increase on higher securitization rate of nonjumbo loans, I construct a similar measure of county securitization rate that only involves nonjumbo loans, and use it as an additional control variable in the baseline specification. This variable captures the regional variation in the increased number of securitized nonjumbo loans due to the effect of CLL change. After controlling for this variable, I obtain very similar results as in columns 5, 6 and 11, 12 of Table 8.

If the increase of credit supply were driven by the increase of bank liquidity, then county securitization rate as a control variable would absorb much variation in approval rate changes, leaving the variable of interest less significant. However, columns 5 and 6 in Table 7 show that after controlling for county securitization ratio, the coefficient of interaction term remains negative and statistically significant. In addition, the magnitude of the coefficient is even larger than the results in Table 2.

1.4.3.4 House price expectation

Another possible alternate explanation for the increase in jumbo approval rate could be due to an expectation of the increase in future house prices. Higher house price growth expectations lower the estimated loss given default, thereby enabling lenders to increase credit supply and target riskier clients ([136]). If this expectation-based hypothesis were the case, then the finding of credit supply increase would be more prevalent in counties with higher expectation of house prices.

One way to test this hypothesis is to focus on areas where the expectations-based channel is not prevalent. [85] point out that areas with extremely elastic housing supply are unlikely to have large increases in house price growth expectations because any upward pressure on house prices will lead to increased construction and thereby a higher quantity of housing stock. Therefore, in very elastic counties house price growth is bounded by the quick adjustment in housing stock.

I test the expectations-based hypothesis by focusing on counties with high housing supply elasticity. I collect data on housing supply elasticity from [157] at the MSA level, and assign the elasticity measure to counties overlapping with the MSAs. This measure of elasticity is based on the percentage of land which cannot be developed for housing, and captures the extent to which the area is land-constrained by its geography. [157] computes and ranks the measure of supply elasticities for 95 MSAs. I focus on the counties with high housing supply elasticity measures in the top tercile (where the measure of supply elasticity is greater than 2.21).[14]

Panel A of Table 9 provides results for the high-elasticity subsample after running the baseline regression in Equation (1). The results show no significant change in the coefficient of the interaction term. The coefficient remains statistically and economically significant for both count-based and volume-based approval rates. This finding indicates that the increased jumbo approval rates in low-income counties after the CLL change are not driven by areas with low housing supply elasticity, thereby suggesting evidence against the increasing house price expectation hypothesis.

1.4.3.5 Demand channel

One may have a concern that the in jumbo loan approval rate can be driven by the income-based demand hypothesis which argues that the growth in individual mortgage size is strongly positively related to the growth in household income ([80]; [4]). If this were the case, then the counties with low household income growth should be less likely to experience a growth in mortgage credit.

To test this hypothesis, I obtain data on county-level per capita income and the growth in per capita income from the Bureau of Economic Analysis over the sample period 2005-2007. Then I focus on the counties with low per capita income (growth), i.e., the counties with per capita income (growth) lower than its median value of the full sample. In particular, the counties with low income growth have average annual nominal growth rate of 1.27%, which suggests a real growth rate of -1.89% (the average inflation rate during this period is 3.16%). Correspondingly, if the increase of credit supply can be explained by the income-based demand hypothesis, then we should not find such jumbo mortgage credit growth in areas with low income growth.

Panels B and C of Table 9 present the results. Panel B (Panel C) rerun the baseline regression in Equation (1) for the counties with low per capita income (growth). In

[14] See [157] for more details on the measure of housing supply elasticity.

Table 9: Alternative explanations: home price expectation and the demand channel

This table examines changes in the jumbo mortgage credit supply before and after the increase of conforming loan limit (CLL) in 2006 and runs baseline regressions on different subsamples to test the home price expectation hypothesis and the jumbo mortgage borrower income (demand) hypothesis. The dataset is at the county-year level from 2005 to 2007. Panel A reports the regression estimates on high land supply elasticity subsample, i.e., counties that overlap with metro statistical areas (MSAs) with the land supply elasticities higher than 2.21 from Table VI in Saiz (2010). Panel B (C) reports the regression estimates on low income (growth) subsample that comprises counties with per capita income (growth rate) lower than its median value. The dependent variable in Panels A, B, and C columns 1-4 (5-8) is the number-(volume-)based jumbo mortgage approval rate. *County Income* is county per capita income obtained from the Bureau of Economic Analysis (BEA). *Log(County Income)* is the logarithm of county per capita income. The indicator variable *Post* takes the value 1 for two entire years from 2006 to 2007 and 0 for the year of 2005. Columns 3, 4, 7, and 8 include borrower, bank, and county controls. Borrower controls include applicant income and loan-to-income ratio. County controls include county income growth, minority fraction, and female fraction. Bank controls include total assets, leverage, accounting profits, liquidity, deposit ratio, deposit costs, letters of credit, C&I loans, and real estate loans. All regression controls are defined in Appendix A. All regressions include county fixed effects and year fixed effects. Standard errors in parentheses are clustered at the county level. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Panel A. Land supply elasticity and jumbo mortgage approval rates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	High Supply Elasticity				High Supply Elasticity			
Dep. Var.	Jumbo AR (Count)				Jumbo AR (Volume)			
County Income*Post	-0.004***		-0.003**		-0.004***		-0.003**	
	(0.001)		(0.001)		(0.001)		(0.001)	
County Income	0.005		0.001		0.003		0.002	
	(0.006)		(0.008)		(0.007)		(0.008)	
Log(County Income)*Post		-0.135***		-0.119***		-0.143***		-0.140***
		(0.040)		(0.044)		(0.046)		(0.049)
Log(County Income)		0.216		-0.012		0.126		0.117
		(0.274)		(0.297)		(0.334)		(0.353)
Observations	465	465	465	465	465	465	465	465
Borrower Controls			Yes	Yes			Yes	Yes
Bank Controls			Yes	Yes			Yes	Yes
County Controls			Yes	Yes			Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R2	0.218	0.222	0.211	0.215	0.262	0.265	0.248	0.252

Table 9: (Cont.) Alternative explanations: home price expectation and the demand channel

Panel B. Borrower income and jumbo mortgage approval rates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Low Income Subsample				Low Income Subsample			
Dep. Var.	Jumbo AR (Count)				Jumbo AR (Volume)			
County Income*Post	-0.021***		-0.021***		-0.021***		-0.022***	
	(0.005)		(0.005)		(0.005)		(0.005)	
County Income	0.034***		0.030*		0.035***		0.034**	
	(0.013)		(0.016)		(0.013)		(0.016)	
Log(County Income)*Post		-0.444***		-0.448***		-0.447***		-0.455***
		(0.120)		(0.121)		(0.123)		(0.125)
Log(County Income)		0.790**		0.700*		0.818**		0.814**
		(0.312)		(0.385)		(0.319)		(0.385)
Observations	3,323	3,323	3,323	3,323	3,323	3,323	3,323	3,323
Borrower Controls			Yes	Yes			Yes	Yes
Bank Controls			Yes	Yes			Yes	Yes
County Controls			Yes	Yes			Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R2	0.089	0.089	0.094	0.093	0.091	0.09	0.098	0.097

Panel C. Borrower income growth and jumbo mortgage approval rates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Low Income Growth Subsample				Low Income Growth Subsample			
Dep. Var.	Jumbo AR (Count)				Jumbo AR (Volume)			
County Income*Post	-0.007***		-0.004**		-0.007***		-0.005***	
	(0.002)		(0.002)		(0.002)		(0.002)	
County Income	0.007*		0.008		0.010**		0.012**	
	(0.004)		(0.005)		(0.005)		(0.005)	
Log(County Income)*Post		-0.212***		-0.128**		-0.225***		-0.147**
		(0.053)		(0.058)		(0.054)		(0.060)
Log(County Income)		0.212		0.194		0.302*		0.319
		(0.174)		(0.204)		(0.177)		(0.200)
Observations	2,681	2,681	2,681	2,681	2,681	2,681	2,681	2,681
Borrower Controls			Yes	Yes			Yes	Yes
Bank Controls			Yes	Yes			Yes	Yes
County Controls			Yes	Yes			Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R2	0.177	0.177	0.202	0.202	0.206	0.206	0.236	0.236

both Panels B and C the coefficients of the interaction term remain negative and statistically significant, which confirms that even in the counties with negative real income growth rate, the increase in jumbo approval rate is still significant. Thus, it cannot be that the results are driven by the income-based demand explanation.

1.4.3.6 Placebo test

Having put forward the idea that the increase in jumbo approval rate is associated with the reduction in jumbo share caused by the CLL change in 2006, the main results in Table 2 are in line with this view, but it is possible that the significant increase of jumbo loan credit is not specific to this sample period. If the credit supply can be explained by other factors instead of the CLL change, we may expect to find such growth in jumbo mortgage credit during period when there is no CLL change.

To show the uniqueness of the impact of the CLL change on jumbo mortgage credit supply, I perform a placebo test on data over Jan 2006-Dec 2007. This period starts right after the new CLL became effective at the beginning of 2006, and ends before the CLL change in "High-Cost" areas determined by the FHFA beginning in 2008. Therefore, the CLL remained unchanged for all counties during this placebo period. However, I assume that there is a CLL increase at the beginning of 2007 and recalculate the independent variables accordingly. For example, Post indicator during this placebo period is equal to one for 2007, and zero for 2006. Particularly, the placebo regression runs the baseline specification in Equation (1) on the placebo period using redefined independent variables.

Table 10 presents the results. Columns 1 and 2 show the baseline regression and the placebo regression for the count-based approval rate as the dependent variable. Column 3 then presents the result from the one-sided t-test that examines whether the coefficient of the interaction term in the baseline regression (column 1) is significantly larger in magnitude than that in the placebo specification (column 2). When

Table 10: Regional variation in lender responses to uniform CLL increase: a placebo test

This table compares our baseline results in columns 1 and 4 with similar estimations for an alternative sample period. The results in columns 2 and 5 are based on panel regressions over the period from 2006 to 2007 ("Placebo"). The dependent variable in columns 1-2 (4-5) is the number-(volume-)based jumbo mortgage approval rate. *County Income* is county per capita income obtained from the Bureau of Economic Analysis (BEA). In columns 1 and 4 (2 and 5) the indicator variable Post takes the value 1 for two entire years from 2006 to 2007 (2007) and 0 for the year of 2005 (2006). Other regression controls are defined in Appendix A. All regressions include county fixed effects and year fixed effects. Standard errors in parentheses are clustered at the county level. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively. Columns 36 show p-values of one-sided t-tests to check whether the estimated coefficients based on different sample periods are significantly different.

	(1)	(2)	(3)	(4)	(5)	(6)
			T-test (p-value)			T-test (p-value)
	Jumbo AR (Count)		Baseline	Jumbo AR (Volume)		Baseline
Dep. Var.	Baseline	Placebo (06-07)	>Placebo	Baseline	Placebo (06-07)	>Placebo
County Income*Post	-0.005***	-0.001	0.00	-0.005***	-0.001	0.00
	(0.001)	(0.001)		(0.001)	(0.001)	
County Income	0.015***	0.010		0.016***	0.011	
	(0.004)	(0.008)		(0.004)	(0.008)	
Observations	7,506	4,770		7,506	4,770	
County FE	Yes	Yes		Yes	Yes	
Year FE	Yes	Yes		Yes	Yes	
Adj. R2	0.160	0.112		0.156	0.0948	

we compare columns 1 and 2, it becomes clear that most of the results are absent in the placebo period. Not only is the statistical significant of the coefficient absent in column 2, but also the magnitude shrinks (-0.005 in column 1 versus -0.001 in column 2). The very low p-value in column 3 formally shows that there is no significant increase of jumbo loan credit in low-incomeareas when the CLL has not changed. Columns 4-6 use the volume-based approval rate as the dependent variable and confirm the robustness of the results.

Overall, Table 10 reflects the uniqueness of the relationship between jumbo approval rate increase in low-income areas and the CLL change. This supports the claim that the impact of reduced jumbo mortgage share on jumbo credit supply either appeared or strengthened, in economic and statistical terms, due to the CLL change.

1.4.3.7 Other robustness checks

Table 11 presents a battery of robustness tests to check whether or not our main results are sensitive to changes in estimation techniques or variable definitions. First, if credit supply has a trend over our sample years, the regression estimation would not capture the *real* impact of CLL change on credit supply. Columns 1 and 5 show regression results where I include a linear time trend that is identical across all counties. In order for the time trend to be reflected in the regression, I drop year fixed effects. The estimations show that the results still hold. This suggests that the coefficient of the interaction term is not driven by the overall direction the credit supply moves across time.

Next, I verify that my findings are not an artifact of state-specific trends across time. Columns 2 and 6 in Table 11 show the results of regression specifications where I control for state-specific time trends. These results survive after including state-specific time trends that allow each state to have different trends in jumbo loan credit supply that could have coincided with the impact of CLL change on local areas.

In columns 3 and 7 I exclude counties with the lowest (i.e., bottom quartile) median income and rerun the baseline specification. In this way I check whether our results are driven by extremely high approval rates for jumbo loans in very-low-income counties where there are only a few jumbo loan applications. This turns out not to be the case and the results are robust to the exclusion of very-low-income counties.

Furthermore, I exclude all extreme values in the 1_{st} and 99_{th} percentile of the distribution of $ApprovalRate$ for both count- and volume-based measures. The results in columns 4 and 8 show that our findings do not appear to be sensitive to the way I exclude extreme values. The coefficients of interaction terms remain negative and statistically significant.

Table 11: Regional variation in lender responses to uniform CLL increase: robustness checks

This table shows robustness tests for our baseline regressions to explain the regional heterogeneity of jumbo loan approval rates after the conforming loan limit (CLL) increased in 2006. It is estimated using baseline regressions and the dataset is at the county-year level from 2005 to 2007. Columns 1 and 5 include a linear time trend that is identical across all counties and drop year fixed effects. Columns 2 and 6 include state-specific time trends that allow each state to have different trends in jumbo loan credit supply and drop year fixed effects. Columns 3 and 7 are based on regressions that exclude the lowest income counties (i.e., bottom quartile). Columns 4 and 8 are based on a sample that excludes extreme approval rates (1% of the distribution on both sides). The dependent variable is number-(volume-)based jumbo loan approval rate in columns 1-4 (5-8). *County Income* is county per capita income obtained from the Bureau of Economic Analysis (BEA). The indicator variable *Post* takes the value 1 for two entire years from 2006 to 2007 and 0 for the year of 2005. All regressions control for borrower, bank, and county characteristics that are defined in Appendix A. All models include county fixed effects. Columns 3, 4, 7, and 8 also include year fixed effects. Standard errors in parentheses are clustered at the county level. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.	Jumbo AR (Count)				Jumbo AR (Volume)			
	Time Trends	State-Time Trends	Excluding lowest income counties	Excluding Extreme AR	Time Trends	State-Time Trends	Excluding lowest income counties	Excluding Extreme AR
County Income*Post	-0.006***	-0.004***	-0.004***	-0.002***	-0.006***	-0.004***	-0.004***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
County Income	0.014***	0.011***	0.013***	0.006***	0.016***	0.012***	0.015***	0.010***
	(0.004)	(0.004)	(0.004)	(0.002)	(0.004)	(0.004)	(0.004)	(0.002)
Post	0.156***	0.115***			0.180***	0.135***		
	(0.036)	(0.037)			(0.037)	(0.038)		
Year	0.028**				0.021			
	(0.013)				(0.013)			
Observations	7,506	7,506	5,507	4,509	7,506	7,506	5,507	4,509
Time Trends	Yes				Yes			
State-Time Trends		Yes				Yes		
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE			Yes	Yes			Yes	Yes
Borrower Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R2	0.151	0.157	0.211	0.346	0.156	0.161	0.210	0.332

The dependent variable in columns 1-4 is number-based jumbo loan approval rate. Columns 5-8 use volume-based approval rate as the dependent variable and further confirms its robustness. In addition, I use the logarithm of county income in the regressions and confirm the robustness.

1.5 Heterogeneity in Lenders and Borrowers

The analysis thus far has focused on the average response of lenders to jumbo mortgage share reductions, suggesting that lenders significantly raise jumbo approval rates in counties where the jumbo share reduction is larger. In addition, it is important to understand heterogeneity in lenders' responses to CLL change, and the difference in approval rates for heterogeneous borrowers. For instance, locally concentrated lenders may be especially sensitive to changes in jumbo market shares; less wealthy and liquidity constrained borrowers may obtain more credit when lenders increase jumbo credit supply. In this section, I aim to identify important heterogeneity in lenders' responses to jumbo mortgage share reductions and heterogeneity in borrowers' characteristics.

1.5.1 Heterogeneous lenders

While the effect of the CLL change differs across regions, lenders in each region may also very in characteristics such as liquidity and local informativeness and thus can differ in their responses to the policy shock. As noted in [129], jumbo loans are (i) less liquid in the capital market than conforming loans, since the latter can be securitized through GSEs and trading of mortgage-backed securities (MBSs) in the secondary market, and are (ii) more private-information-intensive because they are more costly to sell. Therefore, the importance of jumbo market to banks may vary with bank-specific conditions. For example, small banks may differ from large banks in reacting to the CLL change due to differentials in geographic diversification and business bases; banks with differential informativeness of local markets may have different incentives to defend market share.

1.5.1.1 Lender size: small vs. large banks

I first exploit lender size. To classify banks as small or large, I divide the sample of banks based on total assets in 2005 (the first year in the sample period of my analysis). A bank is classified as *large* if the total assets is above the top one percent cutoff of the assets distribution, and classified as *small* if it below the top one percent cutoff.

I have several reasons to exploit variation in bank size: (i) Small banks are more likely to rely on the originate-and-hold business model and thus keep jumbo mortgages on their balance sheets, which lowers the liquidity of their portfolio; (ii) as jumbo mortgage rates are higher relative to conforming loans and thus serve as an important source of income for small banks that do not have many other sophisticated means in generating profits; (iii) small banks tend to be more locally concentrated, therefore they have stronger desire to maintain business connection with their local wealthy borrowers since they cannot easily find substitution in other regions.

Panel A of Table 12 tests the hypothesis that the CLL policy shock should affect small banks more than large banks by running the baseline specifications for small banks (columns 1-4) and large banks (columns 5-8) separately. In columns 1-4 (columns 5-8) I only focus on the subsample of jumbo loan applications to small (large) banks and recalculate the approval rate and the corresponding borrower characteristics as control variables. The negative and significant coefficient on the interaction term for all columns 1-4 confirms that the jumbo share reduction leads to a higher approval rate of jumbo loans for small banks, and this result is robust to the inclusion of a large set of control variables. Columns 5-8 show that the top one percent largest lenders do not increase jumbo credit supply significantly in low-income areas after the CLL change. The results in Table 12 suggest that small banks lend more aggressively than large banks when the pool of jumbo loan borrowers shrinks.

1.5.1.2 Lender informativeness

I next exploit informativeness heterogeneity across bank-county pairs. If banks differ in the extent to which they are informed of local credit markets, they can differ in the strategic use of information to defend market share of jumbo loans.

Theory suggests that the strategic role of acquiring information in jumbo loan segment may interact with the structure of the banking industry. Banks lending in a competitive credit market can differ from those lending in a relatively concentrated

Table 12: Heterogeneity in lenders and jumbo approval rate increase

This table examines changes in the jumbo mortgage credit supply before and after the increase of conforming loan limit (CLL) in 2006 and runs baseline regressions on different subsamples to examine the heterogeneity of lender size. The dataset is at the county-year level from 2005 to 2007. In Panel A, columns 1-4 (5-8) are based on a subsample that includes jumbo loan applications to small (large) banks. A bank is classified as large if the total assets is above the top one percent cutoff of the assets distribution, and classified as small if it below the top one percent cutoff. The dependent variable in columns 1-4 (5-8) is the number-based jumbo mortgage approval rate calculated using the subsample of small (large) banks. *County Income* is county per capita income obtained from the Bureau of Economic Analysis (BEA). *Log(County Income)* is the logarithm of county per capita income. The indicator variable *Post* takes the value 1 for two entire years from 2006 to 2007 and 0 for the year of 2005. Columns 3, 4, 7, and 8 include borrower, bank, and county controls. Borrower controls include applicant income and loan-to-income ratio. County controls include county income growth, minority fraction, and female fraction. Bank controls include total assets, leverage, accounting profits, liquidity, deposit ratio, deposit costs, letters of credit, C&I loans, and real estate loans. All regression controls are defined in Appendix A. All regressions include county fixed effects and year fixed effects. Panels B and C estimate a first-difference cross-sectional regression. The dependent variable in columns 1-2 (3-4) is the change in number-(volume-) based jumbo mortgage approval rate before (i.e., in 2005) and after the CLL increase at the beginning of 2006 (i.e., in 2006 and 2007). In Panel B, *Inform_Num* is defined as the logarithm of the number of jumbo loans that a bank issued in a county in 2005. In Panel C, *Specialty_Num* is defined as the ratio of number of jumbo loans issued by a lender to a county over the number of nonjumbo loans issued by the lender to the county, in the year of 2005. *Jumbo HHI* is the Herfindahl-Hirschman index (HHI) in 2005 computed by summing up the square of each bank's market share in a county, where market share of the bank is defined as the ratio of the number of jumbo loans issued by the bank over the total number of issued jumbo loans by all banks in the given county in 2005. Standard errors in parentheses are clustered at the county level. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Panel A. Lender size

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.	Small Banks' Jumbo AR (Count)				Large Banks' Jumbo AR (Count)			
Log(County Income)*Post	-0.053**		-0.073***		-0.004		-0.045	
	(0.024)		(0.028)		(0.026)		(0.029)	
Log(County Income)	0.068		-0.052		0.217		0.330*	
	(0.125)		(0.169)		(0.167)		(0.194)	
County Income*Post		-0.001**		-0.002**		-0.001		-0.002**
		(0.001)		(0.001)		(0.001)		(0.001)
County Income		0.003		0.001		0.007*		0.009**
		(0.003)		(0.004)		(0.004)		(0.004)
Observations	5,877	5,877	5,877	5,877	5,419	5,419	5,419	5,419
Borrower Controls			Yes	Yes			Yes	Yes
County Controls			Yes	Yes			Yes	Yes
Bank Controls			Yes	Yes			Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R2	0.230	0.229	0.235	0.234	0.139	0.139	0.141	0.141

Table 12: (Cont.) Heterogeneity in lenders and jumbo approval rate increase

Panel B. Lender informativeness

	(1)	(2)	(3)	(4)
Dep. Var.	Δ Jumbo AR (Count)		ΔJumbo AR (Volume)	
Inform_Num*Jumbo HHI	0.016***	0.016***	0.016***	0.016***
	(0.003)	(0.003)	(0.003)	(0.003)
Inform_Num	-0.094***	-0.095***	-0.094***	-0.095***
	(0.020)	(0.020)	(0.020)	(0.020)
ΔLog(Applicant Income)		-0.051***		-0.058***
		(0.010)		(0.010)
ΔLog(LTI Ratio)		-0.069***		-0.071***
		(0.011)		(0.012)
ΔMinority Fraction		-0.037**		-0.034**
		(0.017)		(0.017)
ΔFemale Fraction		0.002		0.000
		(0.012)		(0.013)
Observations	50,094	49,853	50,094	49,853
Borrower Controls		Yes		Yes
County FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Adj. R2	0.117	0.118	0.111	0.113

Panel C. Lender specialty

	(1)	(2)	(3)	(4)
Dep. Var.	ΔJumbo AR (Count)		ΔJumbo AR (Volume)	
Specialty_Num*Jumbo HHI	-0.017***	-0.018***	-0.017***	-0.017***
	(0.489)	(0.495)	(0.490)	(0.496)
Specialty_Num	-0.197***	-0.202***	-0.199***	-0.204***
	(0.034)	(0.035)	(0.034)	(0.035)
ΔLog(Applicant Income)		-0.046***		-0.052***
		(0.010)		(0.011)
ΔLog(LTI Ratio)		-0.068***		-0.072***
		(0.012)		(0.012)
ΔMinority Fraction		-0.033*		-0.030*
		(0.018)		(0.018)
ΔFemale Fraction		0.009		0.009
		(0.013)		(0.013)
Observations	60,344	60,037	60,344	60,037
Borrower Controls		Yes		Yes
County FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Adj. R2	0.0946	0.0951	0.0927	0.0934

market. As jumbo loan market is information-intensive ([129]), banks' acquisition of proprietary information serves a dual role. First, by conducting credit assessment, banks can attract customers from their rivals, and thus extending market share. Second, it allows banks to create an adverse selection problem for their competitors, thereby softening price competition ([94]).[15] I expect that the severity of this problem increases with the degree of credit market competition.

Using the CLL change as an exogenous event that triggered a sudden reduction in jumbo loan shares, I compare the pre-2006 and post-2006 periods in a first-difference cross-sectional setting. By doing so I can test whether the interaction of banks' informativeness and market competitiveness is associated with the increase in jumbo approval rate. To measure the bank's informativeness of a given county, I follow [51] and use the log of the number (or volume) of jumbo loans that a bank provided to a county in 2005 (before the CLL change at the beginning of 2006). The log-transformation captures the decreasing marginal impact of number (or volume) of loans on bank's informativeness. To measure competitiveness of the credit market, I compute the Herfindahl-Hirschman index (HHI) in 2005 by summing up the squared banks' market shares in a county, where market share of the bank is defined as the ratio of the number of jumbo loans issued by the bank over the total number of issued jumbo loans by all banks in the county in 2005.[16]

I use fixed effects to address the unobservable heterogeneity concern. In order to precisely control for changes in credit demand at the county level, I first use county fixed effects to focus on differences across banks within counties (see [114], [159], and [51] for a similar application). This is important because the CLL change may impact the jumbo loan credit demand to varying degrees in different counties. Second, since

[15] As noted in [56], for each bank the adverse selection problem stems from its inability to discriminate between new borrowers and borrowers rejected by its competitors.

[16] I also compute the HHI using market shares based on jumbo loan volumes, and obtain similar results.

banks are active in multiple countries, I include bank fixed effects to control for bank-specific factors that might affect any changes in lending. The combination of bank and county fixed effects allows me to focus on the informativeness measure that links bank i with county j. Since these fixed effects capture (un)observed characteristics of banks and destination counties, concerns about omitted-variable bias should be quite limited.

In particular, the cross-sectional specification is

$$\begin{aligned} \Delta JumboAR_{ij} =& \beta \cdot Inform_{ij} \cdot HHI_j + \gamma \cdot Inform_{ij} \\ & + \zeta \cdot \Delta \textit{Bank-county Controls}_{ij} + \delta_i + \eta_j + \epsilon_{ij}, \end{aligned} \tag{7}$$

where subscripts i and j denote banks and counties, respectively; β is a coefficient vector of the interaction term and is the key variable of interest; $Inform_{ij}$ is the informativeness variable at the bank-county level; HHI_j is the measure of credit market competitiveness at the county level, and its stand-alone base coefficient is absorbed in the county fixed effects; δ_i and η_j are vectors of bank- and county-fixed effect coefficients, respectively; and ϵ_{ij} is the error term. $\Delta JumboAR_{ij}$ is the change in count-based (or volume-based) jumbo loan approval rate (AR) of bank i in county j. In the specification, I also control for changes in bank-county level characteristics such as the applicant income, the loan-to-income (LTI) ratio, the minority fraction, and the female fraction. The applicant income and the LTI ratio are changes in averages across all borrowers that submit applications to bank i in county j.

Panel B of Table 12 presents the results of the cross-sectional specification at the bank-county level. Columns 1-2 show the specifications with count-based AR as the dependent variable. Column 1 shows that the coefficient of the informativeness variable (measured by log of the number of jumbo loans issued) is negative and significant, and the coefficient of the interaction term is positive and significant. Column 2 shows that the result is robust to the inclusion of borrower controls. Columns 3-4 use the alternative volume-based AR as the dependent variable and the results are very similar, both economically and statistically.[17] Overall, the findings indicate that not only do less informed lenders increase their approval rates to jumbo borrowers, but the magnitude of this effect increases with the degree of local credit market competition (measured by county-level HHI).

These results imply that informativeness and competition both play a role in affecting banks' lending strategy. Less informed lenders extend their lending to compete for borrowers and market shares, and they lend more aggressively in the counties where the jumbo credit market is more competitive. These findings are consistent with the view that lending experience gives banks market power over their borrowers ([54]), which they can use to create adverse selection problems for competitor lenders ([56]; and [5]).

1.5.1.3 Lender jumbo loan specialty

In addition to lenders' informativeness that captures the absolute heterogeneity in information advantage across lenders, I then exploit the jumbo loan specialty that focus on relative mortgage concentration within lenders. It is possible that some small banks concentrate more on jumbo loans relative to their conforming loan businesses, even though they may issue less jumbo loan credit in terms of the absolute quantity.

I focus on the variation in banks' jumbo loan specialty for two major reasons. First, since jumbo loans are information-intensive, lenders with jumbo loan specialty have information advantage over their competitors, which provides incumbents with an advantage over new lenders and thereby limits the number of competitors a market can sustain in equilibrium. Second, as noted in [57], the information advantage of some lenders creates adverse selection problems to their competitors and it represents

[17] I furthermore test the robustness to the use of alternative measure of informativeness (i.e., loan volume-based measure) for both count- and volume-based approval rates. The results are available upon request.

an entry barrier. Taken together, given a change in jumbo loan share, banks can use their specialty in jumbo loan segment to strategically compete with their competitors and affect local market structures by extending or reducing mortgage credit.

I measure jumbo loan specialty using the ratio of number (or volume) of jumbo loans issued by a lender to a county over the number (or volume) of nonjumbo loans issued by the lender to the county, in the year of 2005. I then analyze whether the extent to which lenders concentrated on their jumbo mortgage lending before the CLL change would have affected their lending strategy after the CLL change when the overall jumbo share of the residential mortgage market declined.

Specifically, I estimate the following first-difference cross-sectional specification:

$$\begin{aligned}\Delta JumboAR_{ij} =& \beta \cdot Specialty_{ij} \cdot HHI_j + \gamma \cdot Specialty_{ij} \\ &+ \zeta \cdot \Delta Bank\text{-}county\ Controls_{ij} + \delta_i + \eta_j + \epsilon_{ij},\end{aligned} \tag{8}$$

where subscripts i and j denote banks and counties, respectively; $\Delta JumboAR_{ij}$ is the change (from pre-2006 to post-2006 period) in count-based (or volume-based) jumbo loan approval rate (AR) of bank i in county j ; $Specialty_{ij}$ is the jumbo loan specialty variable that is defined above at the bank-county level; HHI_j is the measure of credit market competitiveness at the county level which is defined as in Equation (7); δ_i and η_j are vectors of bank- and county-fixed effect coefficients, respectively; and ϵ_{ij} is the error term.

Panel C of Table 12 presents the results of Equation (8). Columns 1-2 (3-4) show the specifications with the count- (volume-) based AR as the dependent variable. Column 1 shows that the coefficient of the count-based jumbo loan specialty variable and the coefficient of its interaction term with competition measure HHI are both negative and significant. Column 2 shows that the result is robust to the inclusion of borrower controls. Columns 3-4 show that the results are robust to the alternative volume-based AR as the dependent variable.[18]

Overall, the findings indicate that: (i) Lenders that have less expertise in jumbo loans increase their jumbo credit supply to local borrowers, which is consistent with the competition channel that they strategically increase lending to create the adverse selection problem for their competitors; (ii) the magnitude of this effect decreases in the degree of credit market competition at the county level (measured by HHI), which suggests that asymmetric information can determine credit market structure and thus limit the number of competitors a market can sustain in equilibrium.

1.5.2 Heterogeneous borrowers

In this subsection, I examine whether lenders' responses to the CLL change are different across categories of borrowers. Since credit market competition and information asymmetry contribute to determine lenders' responses to the reduction of jumbo loan share across geographical areas, lenders may extend their jumbo credit across different types of borrowers. This may be particularly the case if certain types of borrowers are rationed out when the competition between lenders is less intense.

I first exploit the variation of jumbo loan credit growth across borrower quality. Specifically, I use the loan-to-income (LTI) ratio to proxy for the borrower quality since it provides important hard information in determining a borrower's overall quality (see, e.g., [59]; [113]). The LTI ratio is defined as the ratio of the total amount of jumbo mortgage over the reported applicant income in the HMDA data.[19] I then divide the mortgage origination sample into two groups based on borrower LTI ratios: low quality (LTI ratio above median) and high quality (LTI ratio below median). To

[18] I furthermore test the robustness to the use of alternative measure of jumbo specialty (i.e., loan volume-based measure) for both count- and volume-based approval rates. The results are available upon request.

[19] Some previous studies have pointed out that the applicants' income are upward biased (e.g., [139]). In computing LTI ratio using the reported applicant income from HMDA data I implicitly assume that the income information of jumbo loan borrowers across geographic areas and across different categories is inflated to a similar extent.

examine the heterogeneity in LTI ratios, I run the baseline specification in Equation (1) for the two groups separately.

Panel A of Table 13 reports the results for the high LTI ratio (columns 1-4) and the low LTI ratio (columns 5-8) groups. In Panel A, the coefficient of the interaction variable is negative and significant; in contrast, the coefficient of the interaction term in Panel B are not only less significant but also smaller in magnitude. These results show that after the CLL increase the jumbo mortgage credit growth is higher for the high LTI ratio group. When lenders are looking for opportunities to extend their market shares in a competitive lending environment, they tend to provide more credit to risky jumbo loan borrowers who may have been rationed out in a less competitive lending environment.

I then analyze whether the extent to which banks expand their lending after the CLL change vary across different loan purposes. Anecdotal evidence suggests that it is easier to shop a refinance than a purchase, in part because of the right of rescission under the Truth in Lending Act that protects borrowers, and in part because many lenders are prepared to assume full responsibility for settlement costs which reduces the burden on borrowers.

Other than the above factors, home-purchase loans and refinancing loans may differ from the lender's perspective. For example, it is likely that some borrowers of home-purchase loans are new to the credit market or have been rejected by another lender, which implies higher information-gathering cost or higher risk. In contrast, some refinancing loan borrowers have set up a reliable repayment record and thereby are easier to enter a new mortgage with the same or a new lender. Consistent with this adverse selection channel, I expect to see a strong effect of the CLL change in low-income areas where the competition level is higher after the CLL increase.

Panel B of Table 13 runs the baseline regression in Equation (1) for refinancing mortgage applications (columns 1-4) and home-purchase loan applications (columns

Table 13: Heterogeneity in borrowers: loan-to-income ratios and loan purposes

This table examines changes in the jumbo mortgage credit supply before and after the increase of conforming loan limit (CLL) in 2006 and runs baseline regressions on different subsamples to examine the heterogeneity of borrowers' loan-to-income (LTI) ratios. The dataset is at the county-year level from 2005 to 2007. In Panel A, columns 1-4 (5-8) are based on a subsample that includes borrowers with LTI ratios above (below) the median value of LTI ratio. The dependent variable is the number-based jumbo mortgage approval rate calculated using the corresponding subsample. *County Income* is county per capita income obtained from the Bureau of Economic Analysis (BEA). *Log(County Income)* is the logarithm of county per capita income. The indicator variable *Post* takes the value 1 for two entire years from 2006 to 2007 and 0 for the year of 2005. In Panel B, columns 1-4 (5-8) are based on a subsample that includes only mortgages with the refinancing purpose (home purchase purpose). The dependent variable is the number-based jumbo mortgage approval rate calculated using the corresponding subsample. In both panels, columns 3, 4, 7, and 8 include borrower, bank, and county controls. Borrower controls include applicant income and loan-to-income ratio. County controls include county income growth, minority fraction, and female fraction. Bank controls include total assets, leverage, accounting profits, liquidity, deposit ratio, deposit costs, letters of credit, C&I loans, and real estate loans. All regression controls are defined in Appendix A. All regressions include county fixed effects and year fixed effects. Standard errors in parentheses are clustered at the county level. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Panel A. LTI ratios of borrowers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Borrowers with high LTI ratios				Borrowers with low LTI ratios			
Dep. Var.	Jumbo AR (Count)				Jumbo AR (Count)			
County Income*Post	-0.006***		-0.005***		-0.001*		-0.001*	
	(0.001)		(0.001)		(0.001)		(0.001)	
County Income	0.012***		0.010*		0.002		0.003	
	(0.004)		(0.005)		(0.003)		(0.004)	
Log(County Income)*Post		-0.189***		-0.171***		-0.045*		-0.051*
		(0.025)		(0.029)		(0.024)		(0.027)
Log(County Income)		0.347**		0.233		-0.040		0.108
		(0.144)		(0.217)		(0.128)		(0.172)
Observations	6,705	6,705	6,705	6,705	6,467	6,467	6,467	6,467
Borrower Controls			Yes	Yes			Yes	Yes
Bank Controls			Yes	Yes			Yes	Yes
County Controls			Yes	Yes			Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R2	0.141	0.142	0.154	0.156	0.249	0.250	0.257	0.257

Table 13: (Cont.) Heterogeneity in borrowers: loan-to-income ratios and loan purposes

Panel B. Borrowers with different loan purposes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Refinancing borrowers				Home purchase borrowers			
Dep. Var.	Jumbo AR (Count)				Jumbo AR (Count)			
County Income*Post	-0.005***		-0.005***		0.000		-0.001	
	(0.001)		(0.001)		(0.001)		(0.001)	
County Income	0.017***		0.015***		-0.005		0.000	
	(0.004)		(0.004)		(0.004)		(0.004)	
Log(County Income)*Post		-0.150***		-0.134***		-0.020		-0.025
		(0.024)		(0.026)		(0.025)		(0.027)
Log(County Income)		0.574***		0.547***		-0.177		0.049
		(0.137)		(0.166)		(0.163)		(0.173)
Observations	6,862	6,862	6,862	6,862	5,985	5,985	5,985	5,985
Borrower Controls			Yes	Yes			Yes	Yes
Bank Controls			Yes	Yes			Yes	Yes
County Controls			Yes	Yes			Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R2	0.190	0.191	0.195	0.196	0.112	0.112	0.118	0.118

5-8). In line with expectations, the results show that the jumbo mortgage credit growth is higher for the refinancing mortgage applications than for the ones with the home-purchase purpose.

1.6 Concluding Remarks

In this paper, I analyze the strategic response of lenders facing an exogenous reduction of the jumbo share of local mortgage markets, by exploiting the change in uniform conforming loan limit as the identification strategy. My results establish that, when the local jumbo share is reduced, lenders expand credit to jumbo loan borrowers and compete more aggressively to defend market share. Utilizing rate spread data from HMDA, I also show that banks lower the interest rates of jumbo mortgages especially in areas where the credit market competition is tougher. Furthermore, a larger increase of jumbo approval rate is associated with a relatively poorer future loan performance. My results are consistent with the competition channel that banks give out more jumbo credit without carefully screening borrowers. The effects are especially pronounced in low-income areas where lenders have stronger incentive to defend market share relative to efficiently price the loan. Overall, this paper suggests an unintended consequence of the uniform federal pricing policy that lenders' incentives can be distorted across regions which can further lead to inefficiency of local risk pricing and credit allocation.

Furthermore, on the lender side, smaller banks and banks that are less informed of the local market and that are less specialized in jumbo lending tend to lend more aggressively by expanding credit supply to local borrowers, and the credit expansion grows with competition level of local credit markets. On the borrower side, risky borrowers, i.e., those with higher LTI ratios, and refinancing loans are provided with more credit. In short, my results suggest that lending experience gives banks market power over their borrowers ([54]), which they can use to create adverse selection problems for competitor lenders ([56]; and [5]).

CHAPTER II

HOUSING MARKET INTEGRATION AND ECONOMIC CONVERGENCE

2.1 Introduction

The recent Great Recession highlights the importance of housing market to the U.S. economy. One of the most notable trends in the U.S. housing market in recent decades is that changes in house prices have become increasingly synchronized across regions. The average absolute difference in annual growth rates of Housing Price Index (HPI) across U.S. state pairs decreased from 9.6% in 1975 to 2.5% in 2016. During the same period, a strong economic convergence across U.S. states has also occurred. The average (across state pairs) absolute differences in the growth rates of real Gross State Product (GSP), real income, and total employment have declined significantly at a rate comparable to that of HPI growth.[1] Motivated by these trends, our paper investigates whether and how the inter-state housing market integration may have contributed to the convergence of economic growth across U.S. states.

Several recent studies have documented the increasing co-movement in U.S. house prices across regions and examined the determinants of this trend (e.g., [55]; [47], [45]; [107]; [98]; [117]). The patterns and causes of economic convergence across different countries and regions, on the other hand, have always been an important topic for both policy makers and researchers (e.g., [64]; [13]; [12], [11]; [145]; [14]; [76]; [143]; [106]). Despite the importance of these two phenomena, we are not aware of any

[1] See Figure 4 for details. Housing Price Index (HPI) data are from the Office of Federal Housing Enterprise Oversight (OFHEO). GSP and state income data are from the Bureau of Economic Analysis (BEA). The state-level total employment data are from the Bureau of Labor Statistics (BLS).

research that studies housing market integration as a potential driver of economic convergence.

Both theory and empirical evidence show that the housing market can have a major effect on economic activities. The affordability of real estate and changes of its prices have a direct effect on the wealth and consumption of households ([78]; [135]), a firm's financial capacity ([10], [165], [92]), and regional employment and output ([138]; [3]; [44]; [158]; [130]).

As noted by [20], [115] and [102], the dynamics of asset values interacting with borrowers' credit limits (i.e., the collateral channel) can be a powerful transmission mechanism of production shocks that can be propagated and amplified to other sectors. Supporting the influence of housing market through the collateral channel, [77] and [39] find that firms increase investment following positive price shocks that increase the collateral value of firm assets. A few papers show that increases in housing wealth foster entrepreneurship by allowing individuals to extract more equity from their property to invest in their business (e.g., [3]; [44]; [158]).

We expect the housing market integration to influence the economic synchronization of the states through the collateral channel. First, correlated changes in house prices across states are likely to induce similar changes in collateral values, which introduces related supply and demand shocks in the capital markets of these states. On the supply side, improvements in collateral values alleviate the concerns of lenders on borrowers' debt repayment ability and lower the cost of capital for borrowers. On the demand side, financially constrained individuals and firms will take advantage of the increased collateral values and borrow more to invest in projects that they otherwise do not have capital for. These similar shocks in both the supply and demand sides of capital markets would likely result in related changes in investments, economic growths, and employments, ceteris paribus (e.g., [11]; [76]; [145]).

Second, changes in collateral values can exacerbate business cycles (see [136],

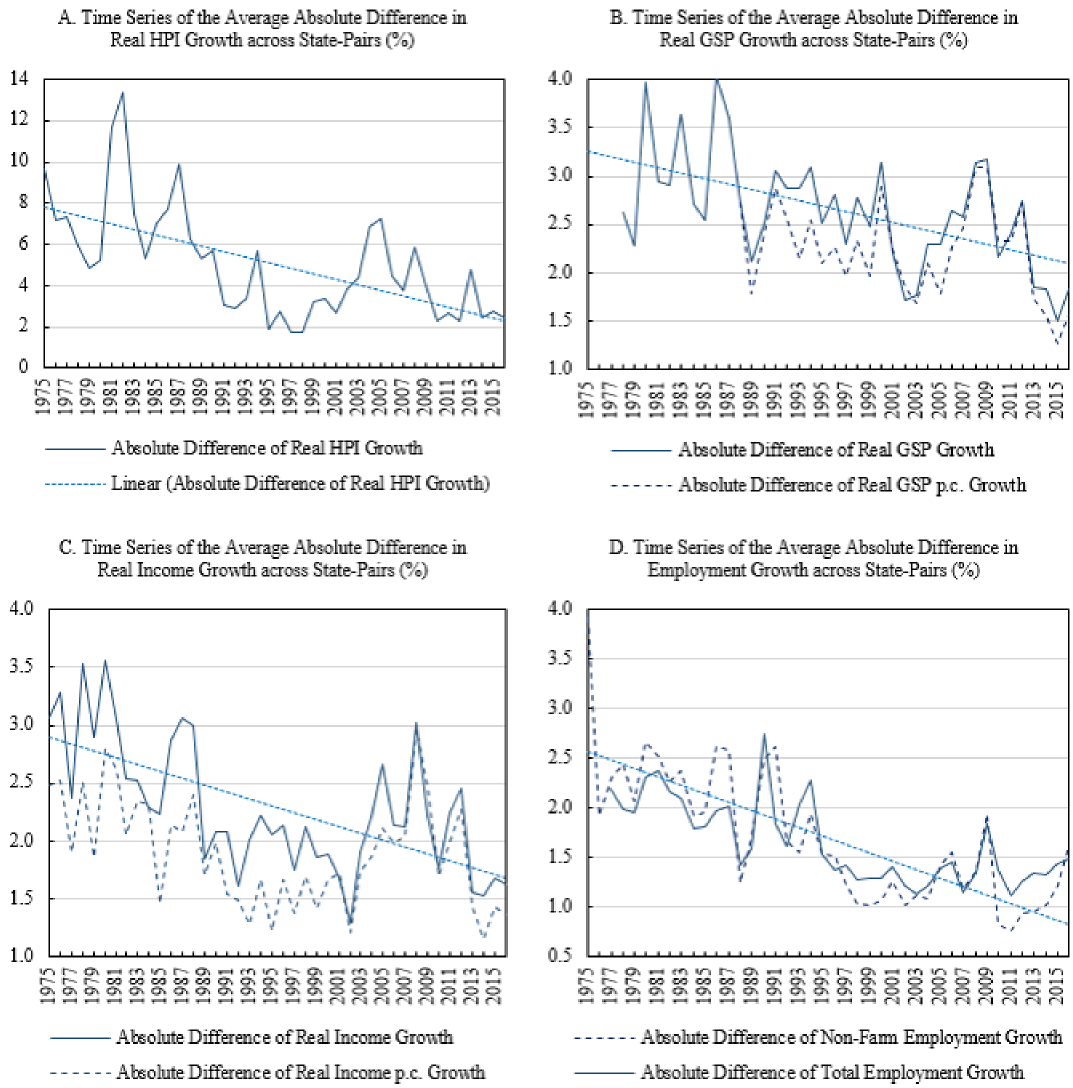


Figure 4: House price growth divergence and real economic growth divergence over 1975-2016

This figure plots the annual averages of HPI growth divergence in Panel A and real economic growth divergence in Panel B-D for the period of 1975 to 2006. HPI growth divergence is the absolute difference in HPI growth rates between a state pair. Real economic growth divergence is the absolute difference in real GSP growth rates between a state pair in Panel B, the absolute difference in real income growth rates between a state pair in Panel C, and the absolute different in employment growth rates between two states in Panel D.

among others). Using a dynamic economy model, [115]) point out that collateral values will deteriorate in business downturns, thus reducing debt capacity and depressing investment, which will amplify the downturn. Moreover, in addition to reducing organic debt borrowing, depreciated house values increase the existing loan to value ratio and may also create the classical debt overhang problem, which affects labor mobility, decreases employment, and reduces investment (e.g., [95]; [62]; [21]; [133]; [26]). During good times, the increasing collateral values will increase firms' debt capacity and investment, which further enhances assets values and strengthens the economic upturn. Given that changes in collateral values can exacerbate business cycle, states that experience similar collateral value shifts may expect to converge in growth patterns and have more synchronized business cycles. Thus, we expect house price integration between states to increase the economic convergence among these states.

Using a panel of all US state pairs from 1976 to 2016, we find a positive and significant relation between house price co-movements and the lagged integration of the states' real GSP growth, real income growth, and total employment growth. These findings are consistent with our hypothesis that real economic convergence follows housing market integration. The economic magnitude is also significant: Moving from the median to the 95th percentile of the housing market divergence distribution leads to seven percentage points, nine percentage points, and four percentage points increase in the median divergence of state GSP growth, income growth, and employment growth, respectively.

Studying the effect of housing market integration on the convergence of state economies faces a number of challenges. First, a positive association between interstate housing market integration and economic pattern co-movement might be spuriously driven by some common omitted variables between states. For example, states with stronger economic, cultural, and political ties may have both more synchronized economic fluctuations and more integrated housing market movements. To mitigate this concern, we include state-pair fixed effects in our regressions, which should remove the influence of state ties that are time invariant. Second, the responses of state economies to nation-wide shocks could be similar. If this is the case, the documented trends in Figure 4 may be simultaneously driven by these nation-wide shocks and result in a spurious correlation between housing market integration and economy synchronization. To address the influence of macro-economic shocks and time series trends, we control for year fixed effects and state specific time trend in our regressions. Third, a concern of reverse causality emerges in that the integration of economic activities may cause housing market integration. For example, [45]) show that income and employment fundamentals contribute to the increases in housing market integration after the housing bubble burst in 2000s. To partially mitigate the concern of reverse causality, we use lagged housing market integration in all our regressions. We also employ an instrumental variable approach to further address these endogeneity concerns.

The ideal instrumental variable (IV) is one that can identify exogenous variations in the co-movements of house prices that are not directly related to real economic activity in these states. To construct the instrument, we rely on foreign shocks to the domestic real estate markets that are orthogonal to the economic development of the states. We extract foreign shocks to the real estate market in a state as the residuals of regressing foreign direct investment (FDI) in the real estate sector of the state on the overall FDI in the state together with state and year dummies. The instrument is then computed as the absolute difference in real estate-related FDI residuals between states i and j in year t. By construction, these residuals are orthogonal to state-level economic conditions and are driven by shocks in foreign countries that lead to investment in the real estate market of U.S. states.[2] The co-movements of these residual FDI flows across states, on the other hand, may induce correlations in house prices in these states. For example, capital flows from China into the housing markets of Georgia and Texas would likely increase the correlation of house prices between these two states. The first stage regression results indeed show that the instrument variable is highly relevant to the inter-state housing market integration. Our IV/2SLS regression estimates confirm that a higher degree of inter-state housing market integration leads to more synchronized state economies. The economic significance suggested by the instrumented coefficients is comparable to that obtained from OLS regressions.

To further establish the validity of our results, we consider some alternative explanations. First, [117]) show that bank integration is a key driver for the increasing co-movements in house prices. Studies have also shown that bank integration affects economic growths (e.g., Morgan et al., 2004). These papers suggest banking integration as a potential hidden factor behind the documented relation between housing market integration and economic convergence. We take two approaches to show that our results are unlikely to be driven by banking integration. First, controlling for banking integration in all regression analyses has no influence on our findings. Next, we show that the significant influence of housing market integration on economic convergence is present in state pairs that were not financially integrated.

Second, state pairs that are geographically close to each other may share strong

[2]For example, the slowdown of Chinese economy and the overheated real estate markets in Canada have driven investors from China and Canada, respectively, to invest in the U.S. real estate market. As reported in the Wall Street Journal (WSJ) article, "Chinese Investors Pour Money Into U.S. Property" (by P. Grant on May 25, 2016), "commercial property sales have slowed in the U.S. this year - but Chinese investors are continuing to plow money into the market", because "the Chinese economy has slumped over the past year. Investors are looking abroad to protect their wealth against the volatility at home". Similarly, the WSJ article "Foreign Buyers Pump Up U.S. Home Prices" (by L. Kusisto on July 18, 2017) reports that "The recent surge in foreign buying was driven largely by Canadians flocking south to escape their own overheated real-estate markets". The overheated real estate market in Canada not only made U.S. home prices "look like a bargain", but also "helps give Canadians the cash to invest in vacation properties to the south".

social, economic, cultural, and political ties, which in turn causes both housing integration and the synchronization of economic activities (e.g., [14]). This argument suggests geographic distance as another potential hidden factor of our findings.[3] To address this concern, we split our sample into two groups based on the median value of state-pair geographic distance and find strong results not only in the group of states that are closely located, but also in the group of states that are located far from each other. This finding suggests that our results are unlikely to be driven by geographic proximity between states.

We next examine whether housing market integration influences economic synchronization through the hypothesized "collateral channel". We employ two tests to confirm the collateral channel. First, we divide industries into collateral-intensive and non-collateral-intensive subgroups within a state and calculate the economic growth divergence measures for these subgroups respectively. We find that the effect of housing integration on economic growth synchronization is particularly strong for the collateral-intensive industries but not significant for the non-collateral-intensive industries. Second, if the economic growth synchronization is related to the housing collateral channel, we should observe increases (decreases) in real estate secured loans in the house-booming (busting) states. To empirically test this conjecture, we compute measures of the prevalence of real estate secured loans in individual states, and find that these measures converge between states as the level of inter-state housing market integration increases. An alternative way of borrowing against real estate assets is using the equity line of credit. Comparing to real estate secured loans, the equity line of credit maybe a more flexible and quicker way for borrowers to tap into their increased house values. Using the home equity line of credit (HELOC) data, we find that the utilization of HELOC converges as the housing markets between states

[3] We measure state distance based on the latitude and longitude points of two state capital cities and employ the "Haversine" formula to calculate the great-circle distance between two points.

become more integrated. Collectively, results based on real estate-secured loans and HELOC provide strong and direct support for the collateral channel.

We then assess two alternative channels through which housing market integration may influence real economic convergence. First, the boom and bust of real estate industry itself could be driving our results, especially for those states, such as Nevada and Florida, where the real estate sector accounts for a large share of state economy. We re-estimate the economic growth synchronization measures after excluding real estate industries and still find strong impact of house price co-movements on the synchronization of the growth rates of non-real estate industries. Second, if increases in house prices improve individuals perception about their future wealth, individuals may increase their current consumption level and drive up local demand for goods ([27]) and employment at non-tradable industries ([138]). Consequently, these local demand shocks instead of collateral shocks may create co-movements in local economic growths. To test for this alternative mechanism, we exclude industries that are most likely to be affected by local demand shocks, i.e., non-tradable industries, and focus our attention on highly tradable industries such as manufacturing and mining that are least influenced by local demand. If our findings are driven by local demand shocks instead of the collateral channel, we would expect the influence of housing market integration on economic synchronization to be significantly affected when we remove from the sample the sectors that are most sensitive to local demand. However, the results show that this is not the case. The direction and significance of the results remain unchanged or even become stronger in some cases when we remove the non-tradable sectors from the regressions.

Our paper adds to a new and growing literature on the increasing housing market integration in the U.S. and across countries ([47] [47], [45]; [107]; [98]; [117]). While these papers focus on documenting the pattern and determinants of the housing market integration, we provide one of the first sets of evidence on the consequence of the housing market integration. A paper that is closely related to ours is [130]. They find that external housing market conditions influence local economic growth in financial connected markets, which they interpret as suggesting that capital flows lead to growth divergence. Our paper differs from theirs in both research question and empirical design. We focus on the convergence of economic growths across states rather than the level of growth in individual states. While the financial market plays a crucial role in our finding through the collateral channel, we do not find that financial integration per se drives the influence of housing market integration on economic convergence.

Our paper builds on the large literature on economic convergence across states in the U.S. (e.g., [64]; [13]; [11]; [24]); [76]). Our results suggest an important new mechanism, i.e., house price co-movement, through which the housing market dynamics could influence the convergence of U.S. state economies.

Our paper also complements the literature that focuses on the importance of the collateral channel in effecting changes in real economic activity (e.g., [20]; [115]; [136]; [39]; [138]; [3]; [158]). More broadly, our findings contribute to a rapidly emerging literature on the relation between housing market and the real economy ([3]; [44]; [130]; [140]; [141]; [158]; to name a few). The turmoil of housing market crisis and the enduring Great Recession have motivated researchers to study how and why housing market influences the real economy. Our evidence shows that the degree of integration is a housing market characteristic that gets transmitted to the other sectors of the economy and the collateral channel is the likely underlying transmission mechanism.

The rest of the paper proceeds as follows: Section 2 describes the data and variable construction. Section 3 discusses the empirical method and results. Section 4 shows the economic mechanism of the collateral channel and examines alternative explanations. Section 5 presents additional robustness checks. Section 6 concludes.

2.2 Data

Our sample includes all possible pairs among 50 U.S. states plus Washington D.C. from 1975 to 2016. It contains yearly measures of housing market integration for state pairs. The state-level Housing Price Index (HPI) used to construct the measures of housing market integration is from the Office of Federal Housing Enterprise Oversight (OFHEO). We measure economic growth convergence between states based on GSP, income, and total employment. The annual values for GSP and state income variables are from the Bureau of Economic Analysis (BEA). The annual state-level total employment data are from the Bureau of Labor Statistics (BLS). The real Gross State Product (GSP) data from the BEA are available from 1987, and thus the first calculated GSP growth rate is for 1988. As a result, the sample period for the baseline regression analysis is from 1988 to 2016. To conduct a robustness check on a longer period, we back out the GSP data from 1977 to 1986 using the time series of Quantity Indexes for Real GDP by state from the BEA. As we will show later, our results are not sensitive to the starting year of the regression sample. We obtain comparable results for alternative samples that start from either 1978 or 1995.

Measures on banking integration between two states are based on the state-level bank lending data from the Call Reports. We use the Federal Deposit Insurance Corporation (FDIC)'s state-level Summary of Deposits data to construct alternative measures of banking integration. We gather other state-level information, such as population and industry composition, from the BEA. Nominal values are converted to real values using the Consumer Price Index "All Items Less Shelter" from the BLS.

2.2.1 House prices co-movement

We retrieve state-level, repeated-sales, quarterly nominal HPI from the OFHEO website (www.fhfa.gov) for the period of 19752016. These data are available for all U.S.

states plus Washington D.C. since 1975.[4] We first calculate quarterly HPI growth rates, and then calculate annual HPI growth rates by compounding quarterly rates. The average annual HPI growth rate by state is reported in Table 14. The average annual HPI growth rate across all fifty states and D.C. is 1.16%. As indicated by the standard deviations of the state-level time-series averages, there is a good amount of variation in HPI growth rates across both states and years.

We follow [106] to construct our integration variables. Specifically, for each state pair, i and j, and each year, t, we construct the divergence of HPI growth rates between the two states using the absolute difference of real annual HPI growth rates:

$$HPI\ growth\ divergence_{ijt} = |HPI\ growth_{it} - HPI\ growth_{jt}|, \tag{9}$$

A lower divergence value indicates a higher housing market integration between the two states. Panel A of Figure 4 presents time series plot of the evolution of housing market integration from 1975 to 2016. As in Landier et al. (2017) and Cotter et al. (2014), we also find a significant downward trend in the HPI growth divergence, suggesting that U.S. housing markets across different states have become more integrated through the years.

We also follow Morgan et al. (2004) to construct three alternative measures of integrations: (i) the correlation of quarterly HPI growth rates between two states over a rolling 5-year (20-quarter) window, (ii) the covariance of quarterly HPI growth rates between two states over a rolling 5-year (20-quarter) window, and (iii) the absolute difference in HPI growth residuals between two states.[5] To compute the growth residuals, we first regress the state-level HPI growth rate on state and year fixed effects, and extract the residuals for each state year. Then we take the absolute difference of the two state residuals as a measure for housing market integration

[4] See Calhoun (1996) and Cotter et al. (2015) for a detailed discussion on the quality and coverage of the HPI index.

[5] Our results are robustness when we use a rolling 3-year (12-quarter) window to estimate the correlation and covariance measures.

Table 14: State-level house price and economic growth rates

This table reports state-level annual averages of the growth rates of house price index (HPI), GSP, income and total employment from 1975 to 2016. The state-level annual averages of HPI growth rates are computed using the quarterly HPI data. GSP Growth, Income Growth, and Employment Growth are average annual growth rates based on Gross State Product (GSP), state income, and total state employment, respectively. Nominal values are converted to real values using the Consumer Price Index from the Bureau of Labor Statistics (BLS).

	HPI Growth (%)		**GSP Growth (%)**		**Income Growth (%)**		**Employment Growth (%)**	
State	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Alabama	0.92	8.93	2.21	2.20	2.42	1.93	0.96	1.99
Alaska	0.09	4.15	2.06	6.63	2.87	5.18	2.04	2.26
Arizona	0.05	4.42	4.16	4.08	4.07	3.25	3.17	2.51
Arkansas	1.28	8.63	2.45	2.39	2.58	2.28	1.12	1.83
California	3.39	9.46	3.22	2.65	3.09	2.49	1.77	2.06
Colorado	2.05	5.45	3.49	2.81	3.57	2.70	2.22	2.17
Connecticut	1.33	7.73	2.43	3.07	2.48	2.64	0.78	1.55
Delaware	3.87	7.90	2.76	3.48	2.55	2.92	1.60	2.09
District of Columbia	0.95	5.85	1.29	1.88	1.79	2.87	0.50	2.87
Florida	1.21	7.78	3.55	2.85	3.69	2.83	2.69	2.33
Georgia	0.25	4.32	3.50	2.85	3.37	2.69	2.05	1.97
Hawaii	3.54	15.88	2.15	2.55	2.33	2.19	1.48	1.82
Idaho	0.46	4.30	3.28	3.58	2.99	2.55	2.04	2.13
Illinois	0.69	6.78	1.84	2.35	1.79	2.22	0.65	1.79
Indiana	0.63	5.36	2.11	3.20	2.00	2.38	0.85	2.26
Iowa	0.08	3.55	2.17	3.11	1.79	2.89	0.63	1.69
Kansas	0.17	3.43	2.09	2.07	2.17	2.13	0.83	1.34
Kentucky	0.52	3.27	1.96	2.73	2.24	2.02	0.76	1.40
Louisiana	0.72	4.35	1.18	3.22	2.39	2.15	0.86	1.78
Maine	2.60	7.77	2.03	2.36	2.35	2.53	1.07	1.79
Maryland	1.55	6.08	2.65	2.04	2.56	2.13	1.33	1.27
Massachusetts	2.23	7.76	2.85	2.77	2.59	2.60	0.87	1.37
Michigan	0.67	6.03	1.24	3.94	1.57	2.89	0.64	2.46
Minnesota	1.23	4.72	2.78	2.68	2.59	2.47	1.27	1.23
Mississippi	0.38	4.08	1.97	2.52	2.29	1.96	0.74	2.09
Missouri	-0.27	4.75	1.91	2.42	2.10	1.88	1.02	1.68
Montana	1.63	5.75	1.93	2.36	2.23	2.47	1.24	1.61
Nebraska	0.65	3.61	2.56	2.53	2.27	2.62	0.86	0.82
Nevada	0.84	7.04	4.26	4.19	4.95	3.69	3.87	2.93
New Hampshire	0.35	3.40	3.68	3.58	3.43	3.28	1.72	2.06
New Jersey	1.34	8.60	2.30	2.47	2.33	2.30	0.96	1.63
New Mexico	1.80	7.39	2.83	3.42	2.98	1.92	1.73	1.92
New York	0.79	4.72	1.99	2.05	2.06	2.30	0.70	1.39
North Carolina	1.63	10.00	3.14	2.63	3.19	2.65	1.63	1.82
North Dakota	1.83	6.78	3.39	6.00	2.32	6.81	1.04	1.66
Ohio	0.07	3.70	1.77	2.74	1.61	2.05	0.54	1.65
Oklahoma	0.26	4.76	2.29	2.72	2.64	2.91	1.12	1.67
Oregon	2.40	7.56	3.55	3.79	2.83	2.58	1.74	2.28
Pennsylvania	0.87	4.66	1.94	1.90	1.92	1.64	0.66	1.35
Rhode Island	2.04	8.59	2.03	2.62	2.11	2.39	0.69	1.88
South Carolina	0.42	3.74	2.99	2.47	2.98	2.05	1.52	1.72
South Dakota	0.78	7.39	3.17	2.94	2.41	3.75	0.98	1.39
Tennessee	0.55	3.62	2.82	2.58	2.91	2.28	1.37	2.07
Texas	0.74	4.33	3.44	2.34	3.77	2.48	2.17	1.25
Utah	1.58	6.11	3.82	2.83	3.87	2.38	2.74	2.03
Vermont	1.14	5.23	2.91	2.81	2.75	2.33	1.33	1.97
Virginia	1.87	14.51	2.83	1.99	3.06	2.14	1.55	1.44
Washington	2.71	6.66	3.12	2.52	3.46	2.50	2.17	2.37
West Virginia	0.70	4.77	1.25	2.20	1.61	1.79	0.35	2.08
Wisconsin	0.65	8.36	2.26	2.06	2.20	1.97	1.00	1.62
Wyoming	1.15	6.12	2.13	3.99	2.92	3.94	1.31	2.59
U.S. Average	1.16	6.28	2.58	2.91	2.65	2.63	1.35	1.86

between the states. As we will discuss in Section 5, our results are robust to these alternative measures of housing market integration.

2.2.2 Measures for real economic convergence

We obtain state-level, annual GSP, income, and employment data from the BEA website (bea.gov). Using these data, we calculate the annual growth rates for GSP, income, and employment. Table 8 presents the state averages of these variables. The average growth rate across 51 regions is 2.58% for GSP, 2.65% for income, and 1.35% for employment. While the variation of these economic growth rates is generally smaller than that of the HPI growth rate, there are still ample variations for these economic growth rates across states.

Similar to the housing market integration measure, for each state pair, i and j, and each year, t, we measure the divergence of economic growth using the absolute difference of real annual economic growth rates:

$$Y\ divergence_{ijt} = |Y_{it} - Y_{jt}|, \tag{10}$$

where Y_{ij} is one of the three economic fundamental growth rates described above. Intuitively, this measure captures how dissimilar economic growth rates are between two states in any given year. A lower value suggests more synchronized economic growth between the two states. Panel B-D of Figure 4 presents time series plots of the evolution of the three real economic synchronization measures from 1977 to 2016. As the trend lines show, the divergences of all growth measures decline from 1977 to 2016. This confirms the well-documented trend in the economics literature that the state economic growths have become more synchronized in the U.S. (e.g., Barro and Sala-i-Martin, 1991, 1992).

To check the robustness of our findings, we construct an alternative measure of real economic synchronization: absolute differences in economic growth residuals between a state pair. In Section 5, we show that our results are robust to these alternative measures of economic synchronization.

2.2.3 Descriptive statistics

Table 15 reports descriptive statistics at the state-pair-year level for the housing market integration and economic growth convergence measures for the period of 1988-2016. The sample size is 36,975, which is the total possible number of state pairs for 51 regions spanning 29 years. The average divergence over the sample period is 2.47% for GSP growth, 2.03% for income growth, and 1.49% for employment growth. By comparison, the average divergence in HPI growth over the sample period is 3.78%.

Table 16 presents the correlation coefficients between HPI growth divergence and the divergence of economic growth rates across states. The correlation between the current or lagged divergence of HPI growth rates and each measure of economic divergence is positive and statistically significant at the 1% level. This supports a positive association between house price co-movements and real economic convergence.

Figure 5 plots the relation between HPI growth divergence and real economic growth divergence measured by GSP, income and employment in Panel A, B, C, respectively. Consistent with a positive correlation between HPI growth divergence and economic growth divergence, the fitted trend lines in all three panels have a positive and statistically significant slope. In the following section, we try to establish a causal effect of housing market integration on real economic convergence by implementing multivariate analysis through multiple approaches.

Table 15: Summary statistics

This table reports summary statistics of the main variables used in the empirical analysis. The sample period is from 1988 to 2016. GSP growth divergence, Income growth divergence, and Employment growth divergence are the absolute difference in real growth rates between any state pair in year t, computed using GSP, income, and total employment, respectively. $RE - securedloans\%$ divergence is the fraction of total real estate-secured loans issued in a state over total bank loans issued in the state; $RE - securedloans\%$ (Assets) divergence is similar but over total bank assets in a state. HPI growth divergence is the absolute difference in Housing Price Index (HPI) growth rates of any state pair in year t. Banking integration is defined for a state pair (i, j) as $\Sigma_k s_k^i \times s_k^j$, where s_k^i is the market share of bank k in state i, in terms of bank assets. Log of GSP product and Log of population product are the logs of the products of two states' GSP and population, respectively. Difference in log GSP is the absolute difference in the logs of two states' GSP for any state pair in year t. GSP growth residual divergence, Income growth residual divergence, Employment growth residual divergence, and HPI Growth residual divergence are the absolute difference in the residuals of growth rates between any state pair in year t, computed using GSP, income, total employment, and HPI growth rates, respectively. The residuals are obtained from regressing the respective growth rates on state and year fixed effects. Nominal values are converted to real values using the Consumer Price Index from the BLS. See Appendix for detailed variable definitions.

Variables	**Obs**	**Mean**	**Std. Dev.**	**5%**	**25%**	**Median**	**75%**	**95%**
Dependent variables								
GSP growth divergence	36975	2.465	2.280	0.200	0.900	1.900	3.400	6.700
Income growth divergence	36975	2.026	1.769	0.140	0.748	1.598	2.836	5.319
Employment growth divergence	36975	1.491	1.288	0.100	0.500	1.200	2.100	3.900
Independent variables								
HPI growth divergence	36975	3.782	3.988	0.208	1.102	2.549	5.090	11.472
Banking integration	36975	0.004	0.018	0.000	0.000	0.000	0.000	0.020
Log of GSP product	36975	23.159	1.493	20.712	22.114	23.139	24.203	25.638
Log of population product	36975	30.074	1.449	27.611	29.036	30.099	31.102	32.432
Difference in log GSP	36975	1.190	0.847	0.098	0.499	1.033	1.732	2.810
Difference in Industry Composition	36975	0.012	0.016	0.002	0.004	0.006	0.012	0.041
Alternative variables:								
RE-secured loans% divergence	30740	0.161	0.137	0.011	0.058	0.124	0.226	0.446
RE-secured loans% (assets) divergence	30780	0.121	0.100	0.008	0.045	0.096	0.173	0.321
GSP growth residual divergence	36975	2.358	2.188	0.156	0.815	1.782	3.259	6.333
Income growth residual divergence	36975	1.905	1.732	0.131	0.668	1.468	2.633	5.132
Employment growth residua divergence	36975	1.335	1.163	0.095	0.485	1.033	1.858	3.590
HPI growth residual divergence	36975	3.803	3.887	0.223	1.150	2.650	5.139	11.326

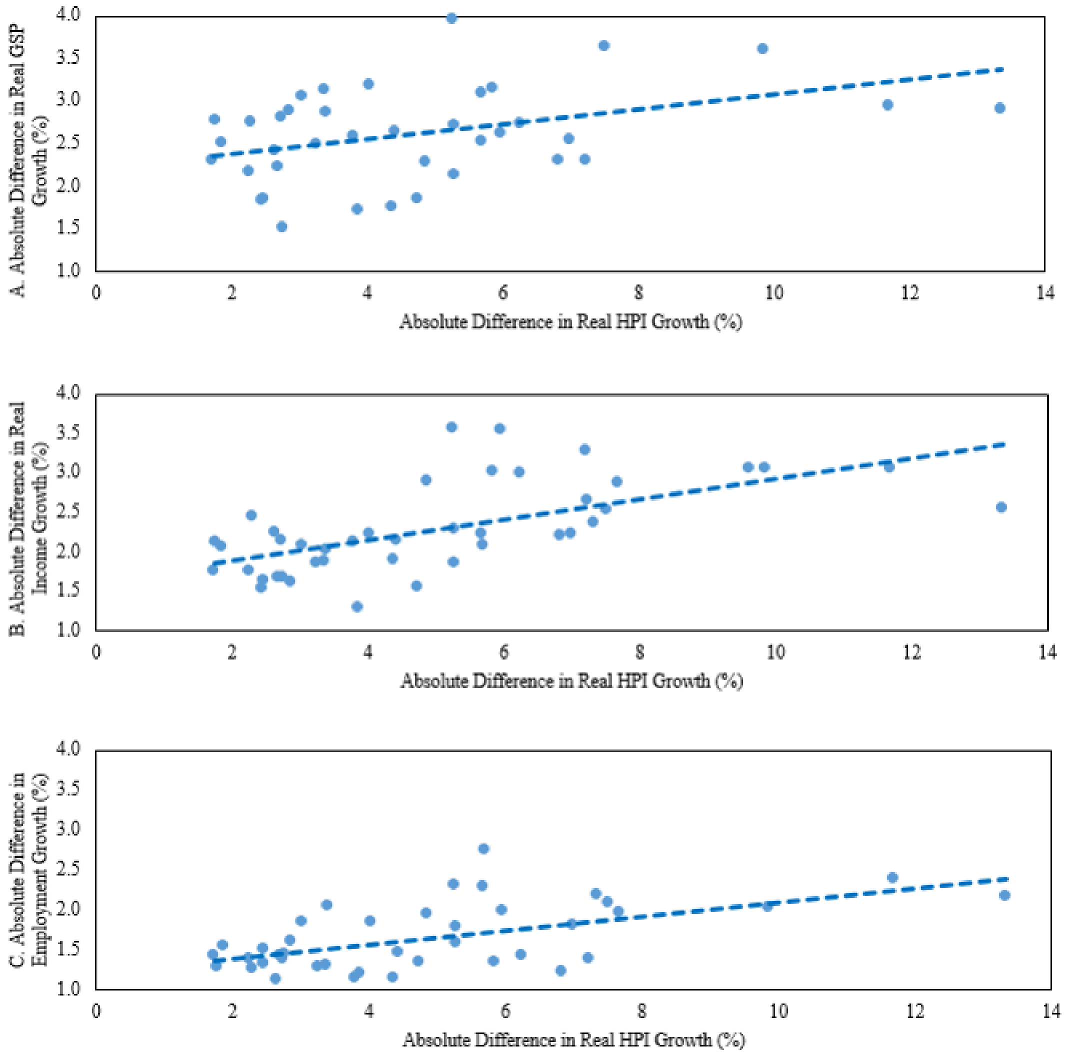


Figure 5: The relation between HPI growth divergence and real economic growth divergence

This figure plots annual averages of real economic growth divergence (Y axis) against HPI growth divergence (X axis) for the period of 1975 to 2016. HPI growth divergence is the absolute difference in HPI growth rates between a state pair. Real economic growth divergence is the absolute difference in real GSP growth rates between a state pair in Panel A, the absolute difference in real income growth rates between a state pair in Panel B, and the absolute different in employment growth rates between two states in Panel C.

Table 16: Correlation matrix

This table reports correlation coefficients between major variables in this study. The variables we consider include the absolute difference in real GSP (p.c.) growth, real income growth, and total employment growth, among state pairs. We extract foreign shocks to the real estate market in a state as the residuals of regressing foreign direct investment (FDI) to the real estate sector of the state on the overall FDI to the state together with state and year dummies.

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1)	AD in Real GSP Growth	1												
(2)	AD in Real GSP p.c. Growth	0.80	1											
(3)	AD in Real Income Growth	0.47	0.27	1										
(4)	AD in Real Income p.c. Growth	0.26	0.33	0.64	1									
(5)	AD in Total Employment Growth	0.17	0.10	0.16	0.08	1								
(6)	AD in Real HPI Growth	0.10	0.05	0.16	0.14	0.07	1							
(7)	AD in Real HPI Growth - lag	0.05	0.02	0.10	0.08	0.05	0.54	1						
(8)	CoHerfindahl - lag	0.02	0.01	0.01	-0.01	0.00	-0.03	-0.04	1					
(9)	Product of Log GSP p.c. - lag	0.05	0.05	0.06	0.11	0.02	0.07	0.01	0.02	1				
(10)	Product of Log Population - lag	-0.16	-0.18	-0.16	-0.18	-0.15	0.00	-0.02	0.00	-0.07	1			
(11)	AD in Log GSP p.c. - lag	0.08	0.07	0.06	0.10	0.23	0.05	0.06	-0.01	0.48	-0.36	1		
(12)	AD in FDI (PPE) Residuals	0.04	0.08	0.00	0.02	-0.02	-0.05	-0.06	0.00	0.03	-0.16	-0.01	1	
(13)	AD in FDI (PPE) Residuals - lag	0.00	0.03	0.06	0.13	-0.03	-0.02	-0.04	0.01	0.00	-0.17	-0.02	0.08	1

2.3 *Housing market integration and the convergence of economic activity*

We use the following multivariate model to examine the influence of house prices integration on economic synchronization:

$$Y\ divergence_{ijt} = \beta \times HPI\ growth\ divergence_{ijt-1} + X'_{ijt-1} \times \Theta + \gamma_{ij} + \delta_t + \epsilon_{ijt}, \tag{11}$$

where $YDivergence_{ijt}$ represents the measures of economic synchronization as defined in equation (2) between states i and j in year t, and $HPIGrowthDivergence_{ijt-1}$ is the measure of house prices integration between states i and j in year $t1$. We also include year fixed effects (δ_t) and state-pair fixed effects (γ_{ij}) in the specification. The year fixed effects account for the effect of market-wide national shocks and other time-varying factors that can affect both housing market integration and economic synchronization patterns in these states. The state-pair fixed effects control for time-invariant factors that are common to both states, such as cultural and political ties, geographic proximity, and similarities in institutional administration and industry structures.

To control for potential serial correlations in the panel data, standard errors are clustered at the state-pair level to allow for arbitrary heteroskedasticity and autocorrelation for each state pair (see also [22]). Furthermore, we control for state-specific linear time trends that allow each state to have different trends in real economic growth that could have coincided with the housing price growth.

Vector X_{ijt1} includes control variables that capture some time-varying factors that may affect the dynamic evolution of real economic synchronization for a state-pair. We control for the level of banking integration between two states because the literature shows that banking integration encourages real economy integration (see, for example, Morgan, Rime, and Strahan, 2004; Michalski and Ors, 2012). We follow Landier et al. (2017) and construct a "Co-Herfindahl" measure to capture bank integration between states. The Co-Herfindahl is defined as the sum of products of banks market shares for a state pair (i, j), i.e., $\Sigma_k s_{ik} \times s_{jk}$, where s_{ik} is the market share of bank k in state i, in terms of total outstanding loans. A higher Co-Herfindahl implies a more integrated banking system. Alternatively, we measure banking integration as the ratio of jointly owned bank loans (or assets) for a state-pair divided by the total bank loans (or assets) for the state-pair. As in Morgan et al. (2004), we calculate jointly owned bank loans or assets at the bank holding company level. The results are very similar for both measures of bank integration. We report results based on the Co-Herfindahl measure.

We also control for several gravity variables that may influence the economic convergence of two states. Using the product of the two states' GSP and population in the previous year, we account for the possibility that our estimates are driven by states' receiving excessive capital investment in real estate industry and at the same time converging to a new steady state. By including the lagged value of the absolute difference in the log p.c. GSP, we control for the possibility that the positive effect of housing integration on real integration is simply driven by the fact that housing integration increases among dissimilar states, which may also experience difference growth patterns since poor states will grow faster than rich states. All control variables are measured in year t-1. The low correlations between HPI growth divergence and other independent variables as shown in Table 15 suggest that multicollinearity is unlikely to be a concern in the regressions.

2.3.1 OLS regression results

Table 17 reports the results of estimating Equation (3) using ordinary least squares (OLS) regressions. The dependent variable is GSP growth divergence in Column 1 and 2, income growth divergence in Column 3 and 4 and employment growth divergence in Column 5 and 6. In columns 1, 3, and 5, we run the regression without controlling for banking integration and the gravity variables. The coefficient of HPI growth divergence is positive and statistically significant at the 1% level in all three models. This result is consistent with our hypothesis that housing market integration increases real economic convergence. In columns 2, 4, and 6, we include in the empirical specification the lagged values of the banking integration measure and gravity variables. The coefficient of banking integration is negative. This confirms the findings in Morgan et al. (2004) and Michalski and Ors (2012) that banking integration promotes real economic integration. While these control variables clearly have significant influence on the real economic growth divergence, including them has no material impact on the coefficient of HPI growth divergence. The coefficient on HPI growth divergence remains positive and statistically significant at the 1% level for all three columns. The influence of HPI growth divergence is economically significant as well. For example, based on the coefficient estimate in Column 2, 4, and 6, moving from the median to the 95th percentile of the housing market divergence distribution leads to seven percentage points, nine percentage points, and four percentage points increase in the median divergence of the two states' GSP growth, income growth, and

Table 17: OLS regressions of real economic convergence on housing market integration

This table reports the OLS regression estimates. The sample period is from 1988 to 2016. The dependent variables are denoted in the column head. GSP growth divergence, Income growth divergence, and Employment growth divergence are the absolute difference in real growth rates between any state pair in year t, computed using GSP, income, and total employment, respectively. HPI growth divergence is the absolute difference in Housing Price Index (HPI) growth rates of any state pair in year t. Log of GSP product and Log of population product are the logs of the products of two states' GSP and population, respectively. Difference in log GSP is the absolute difference in the logs of two states' GSP for any state pair in year t. All independent variables are measure in year t-1. Standard errors are clustered at the state-pair level. *, **, and *** denote statistically difference zero at the 10%, 5%, and 1% significant level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	GSP growth divergence		**Income growth divergence**		**Total employment growth divergence**	
HPI growth divergence	0.016***	0.015***	0.018***	0.017***	0.005***	0.005***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
Banking integration		-1.281*		-0.717		-0.401
		(0.772)		(0.636)		(0.315)
Log of GSP product		3.500***		1.586***		0.199
		(0.302)		(0.186)		(0.138)
Log of population product		-2.957***		0.486		0.364
		(0.737)		(0.511)		(0.391)
Difference in log GSP		-0.217*		-0.083		0.008
		(0.115)		(0.086)		(0.061)
Difference in industry composition		17.629***		8.087***		9.560***
		(3.316)		(2.821)		(2.123)
State-Pair FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State Time Trends	Yes	Yes	Yes	Yes	Yes	Yes
Observations	36,975	36,975	36,975	36,975	36,975	36,975
Adj.R2	0.214	0.222	0.252	0.256	0.200	0.201

employment growth, respectively.

2.3.2 Endogeneity concerns

The OLS results in Table 17 show a strong positive relation between housing growth divergence and economic synchronization. Although this result is robust to a variety of control variables, additional endogeneity concerns may still pose challenges on interpreting the relation as casual.

First, we may not have fully controlled for some time-varying latent variables that may simultaneously influence the housing market integration and real economic convergence across states. For example, the banking integration measure captures the similarity of bank asset shares in two states, but it does not reflect the actual capital flows between the states nor does it tell how well developed are the banking systems in the states. Moreover, while state-pair fixed effects control for the geographic proximity between two states, they do not necessarily capture the possible changes in social, cultural, and economic ties between the states.

Second, a possible concern emerges from reverse causality. Cotter et al. (2014) show that income and employment fundamentals contribute to housing market integration after the housing bubble burst in 2000s. This suggests that converging economic fundamentals between two states may encourage housing market integration. To mitigate the concerns for reverse causality, in our panel estimates we use lagged values of housing growth divergence. However, it is not an ideal solution because (i) business cycles do not shift on a yearly basis, which means that last years economic growth patterns may well continue into later years; (ii) anticipation of converging business cycles between two states can also affect future house prices co-movement.

Third, the HPI data only covers changes in residential real estate prices. Some studies argue that prices changes in the commercial real estate segment are more important for real synchronization than residential real estates prices. If this is the case, it has two implications for our study. First, the fact that we find strong influence using only residential housing prices makes the effect of real estate market on economic synchronization even more robust as the effect of commercial real estate is likely stronger. Second, though commercial indices are highly correlated with residential indices with a correlation coefficient more than 0.5 (Chaney, Sraer, and Thesmar, 2012), there are still some omitted variations in the commercial real estate prices that are not captured by the HPI indices. This measurement error in our variable may introduce an omitted variable bias in our estimation too.

To address these additional endogeneity concerns, we undertake two sets of empirical analyses: (i) the IV/2SLS estimation; and (ii) targeted analyses on a few alternative explanations that are directly related to the potential hidden factors discussed above. The specific empirical approach and findings of these two types of analyses are discussed in the following two subsections.

2.3.3 2SLS/IV estimation

2.3.3.1 Instrumental variable

The various endogeneity problems discussed in the previous section all suggest that the omitted variable bias may be present in our analysis. With a valid instrumental variable, however, one can adequately address the omitted variable bias using the 2SLS estimation approach. The ideal instrumental variable is one that only affects the housing market integration of different states (the relevance restriction), but is not related to the states' real economic convergence through channels other than the housing market integration (the exclusion restriction). Identifying such a valid instrument is very challenging as most policy or regulation shocks to the housing market in the U.S. are often economic policies that are likely to influence the growth of the state economies. Moreover, as the endogeneity issues involve a wide variety of local and nation-wide economic, geographic, and even cultural factors, it is hard to come up with an instrumental variable that is exogenous to all these potential omitted variables. Further adding to the challenge, the instrumental variable should be exogenous to each of the three dependent variables, i.e., the growth rates of GSP, income, and employment.

Given these challenges, we utilize foreign instead of domestic shocks to construct the instrumental variable. To identify foreign shocks to the local real estate markets, we use the foreign direct investment (FDI) data from BEA. Specifically, we employ the annual state-industry level value of "Gross Property, Plant, and Equipment (PPE) of U.S. Affiliates of Foreign Parents" as a proxy for the magnitude of FDI (from all foreign countries) in real estate sector. A states FDI level could be high because of the state's overall economic development is attractive to foreign investors. If this is the case, the FDI to the real estate sector could be endogenous if it simply takes a share in the overall FDI investment as a response to the states economic conditions. To remove the general trend of FDI into a state, we use the following empirical specification:

$$\Delta RE - FDI_{it} = \beta \times \Delta OverallFDI_{it} + \eta \times HPI\ residual_{it} + \gamma_i + \delta_t + \epsilon_{it}, \quad (12)$$

where $\Delta RE - FDI_{it}$ represents the growth rate in real estate-related FDI in state i in year t, and we use $\Delta Overall - FDI_{it}$ to control for the overall growth of foreign investment that reflects state-level economic conditions in state i in year t. In addition, we add state fixed effects (γ_i) and year fixed effects (δ_t). The state effects account for time-invariant factors such as cultural and political ties formed between state i and foreign investors and other unobservable factors that can have an impact on patterns of foreign investment in the real estate industry of state i. The year fixed effects account for the effect of overall worldwide shocks and other time-varying common factors that affect both economic conditions in the U.S. (and in state i) and countries of foreign investors. We also use HPI residual it to account for the fact that real estate industry in state i in year t is particularly attractive to foreign investors. In particular, we use the following specification to estimate HPI growth residuals:

$$\Delta HPI_{it} = \zeta_i + \eta_i + \nu_{it}, \quad (13)$$

where ΔHPI_{it} is the housing price index growth rate in state i in year t. We add state fixed effects (ζ_i) and year fixed effects (η_t) to account for the average house price growth in each state and year, respectively. Thus, ν it is the HPI residual for state i in year t in Equation (4).

We then use the FDI residual, ϵ_{it}, in Equation (4) to construct the instrumental variable for housing market integration. The instrumental variable is the absolute difference of FDI residuals for state i and j, i.e., $AD\ in\ RE - FDI\ Resd_{ijt} = |\epsilon_{it}\epsilon_{jt}|$, where ϵ_{it} and ϵ_{jt} are estimated separately using Equation (4) for state i and j. Because the PPE data series from the BEA is only available till 2007, our instrumental variable is constructed for the period of 1987 to 2007.[6] By construction, the residuals are orthogonal to state-level economic conditions and are driven by shocks in foreign countries that lead to investment in the real estate market of U.S. states. For example, the slowdown of Chinese economy have driven investors from China to invest in the U.S. real estate market. We expect the instrumental variable to relate positively to our interest variable, house prices co-movements, because related residual FDI flows across states is likely to generate correlations in house prices in these states. For example, capital flows from China to the housing markets of Georgia and Texas will likely increase the house price correlation between these two states.

We formally evaluate the validity of the instrumental variable in the following section. We posit the following first-stage relationship between state-pair difference in real estate-related FDI residuals ($AD\ in\ RE{-}FDI\ Resd$ defined above) and housing growth divergence:

$$\begin{aligned} HPI\ growth\ divergence_{ijt-1} =& \beta \times AD\ in\ RE - FDI\ resid_{ijt-1} \\ &+ X'_{ijt-1} \times \Theta + \gamma_{ij} + \delta_t + \theta_{ijt-1}. \end{aligned} \tag{14}$$

The state-pair difference in real estate-related FDI residuals serves as a valid instrument if: i) it is significantly correlated with housing growth divergence, and ii) conditional on other factors, state-pair difference in real estate-related FDI residuals affect economic cycle divergence through housing growth divergence (i.e., $COV(AD\ in\ RE{-}FDI\ Resd_{ijt-1}, \epsilon_{ijt}|X_{ijt-1}, \gamma_{ij}, \delta_t) = 0$, where ijt is the error term in the second stage (Equation (3)). Because lagged values are used in equation (6), the data period for the 2SLS estimation is from 1988 to 2008 as the instrumental variables is available from 1987 to 2007, which includes 20,690 observations. Panel A of Table 18 presents the results of first-stage regressions. As in Table 18, we estimate two models, one

[6]The PPE data becomes available again in 2015 and 2016. We add these two years of data and obtain similar results.

without (Column 1) and one with (Column 2) control variables. The coefficient on RE-FDI resd. divergence is positive and statistically significant at the 1% level in both models. This suggests that states that diverge in the residual growth rates of real estate-related FDI also have higher HPI growth divergence. The intuition is as follows: if state i receives a large amount of real estate FDI that is driven by shocks in foreign countries during certain period and state j does not get these foreign shock induced real estate FDIs, house prices in state i would most likely increase while house prices in state j would remain the same, ceteris paribus. As a result, the growth rates of house prices in states i and j diverge. The Cragg-Donald F statistic is above 10 for both models, suggesting that the instrument is not weak (see Staiger and Stock, 1997; Stock, Wright, and Yogo, 2002).

Panel B of Table 18 reports the second-stage estimates. The dependent variable is GSP growth divergence in Column 1 and 2, income growth divergence in Column 3 and 4, and employment growth divergence in Column 5 and 6. Regardless of whether we include the control variables or not, the coefficient on HPI growth divergence in all columns is positive and statistically significant. This confirms our findings from OLS regressions that real economic convergence follows housing market integration. Moreover, we note that the economic significance implied from the IV/2SLS estimates are comparable to those of OLS estimates. Based on the coefficient estimate in Column 2, 4, and 6, moving from the median value to the 95th percentile of the predicted house price divergence results in four percentage points, twelve percentage points, and four percentage points increase in the median divergence of GSP growth, income growth, and employment growth, respectively.

2.3.3.2 Potential hidden factors: Banking integration and geographic proximity

To further establish the validity of our results, we explore a few alternative explanations for the positive relation between housing market integration and economic

Table 18: IV/2SLS regressions of real economic convergence on housing market integration

This table reports the first stage (Panel A) and second stage (Panel B) results of 2SLS estimates. The sample period is from 1988 to 2008. Panel A reports the first-stage regression results. The dependent variable is the HPI growth divergence. Panel B reports the second-stage regression results. The dependent variables are denoted in the column head. GSP growth divergence, Income growth divergence, and employment growth divergence are the absolute difference in real growth rates between any state pair in year t, computed using GSP, income, and total employment, respectively. All independent variables are measure in year t-1. Standard errors are clustered at the state-pair level. *, **, and *** denote statistically difference zero at the 10%, 5%, and 1% significant level, respectively.

Panel A. First-stage results

	(1)	(2)
	HPI growth divergence	
RE FDI resd. divergence	0.0017***	0.0017***
	(0.00042)	(0.00042)
Banking integration		-0.180
		(0.394)
Log of GSP product		3.674***
		(0.780)
Log of population product		-2.752
		(2.907)
Difference in log GSP		0.286
		(0.298)
Difference in industry composition		5.083
		(7.529)
State-Pair FE	Yes	Yes
Year FE	Yes	Yes
State Time Trends	Yes	Yes
Observations	20,690	20,690
Adj. R2	0.439	0.440

Panel B. Second-stage results

	(1)	(2)	(3)	(4)	(5)	(6)
	GSP growth divergence		**Income growth divergence**		**Total employment growth divergence**	
HPI growth divergence	0.606***	0.597***	0.874***	0.877***	0.217**	0.209**
	(0.208)	(0.208)	(0.254)	(0.256)	(0.092)	(0.092)
Banking integration		-0.537		-3.786**		-0.226
		(1.497)		(1.878)		(0.689)
Log of GSP product		-1.615*		-1.851		-0.465
		(0.968)		(1.189)		(0.435)
Log of population product		-5.339**		3.831		-1.921*
		(2.385)		(2.794)		(1.011)
Difference in log GSP		0.027		-0.428		-0.061
		(0.256)		(0.307)		(0.110)
Difference in industry composition		18.131***		9.932***		14.123***
		(6.290)		(3.495)		(3.235)
State-Pair FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State Time Trends	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,690	20,690	20,690	20,690	20,690	20,690

convergence in this section. The first alternative explanation is that increases in banking integration can lead to both housing market integration (Landier et al. 2017) and real economic convergence (Morgan et al. 2004)) or divergence (e.g., Kalemli-Ozcan et al, 2013; Mian, Sufi, and Verner, 2017b), depending on whether credit supply or credit demand shocks predominate. Thus, banking integration is a potential hidden factor that could simultaneously affect both housing market integration and real economic convergence. Although this concern is mitigated in our analysis as we include a measure of banking integration as a control variable, we employ a subsample analysis to directly examine if banking integration is driving our results. We use the banking integration measure (i.e., Co-Herfindahl) in Landier et al. (2017) and classify a subsample of state pairs as having a low bank integration if the Co-Herfindahl measure between the two states is zero. If banking integration is driving our results, the effect of HPI growth divergence on economic growth divergence should not be present or at least much weaker for this subsample of state pairs. The results are presented in columns 1, 5, and 9 of Panel A for OLS regressions and Panel B for 2SLS estimations in Table 19. The sample period for OLS regressions is from 1988 to 2016. As discussed in Section 3.2.1, due to IV data availability, the sample period for 2SLS regressions is from 1988 to 2008. In untabulated results, we verify that results are similar when we run the OLS regressions in the 2SLS sample. As shown in the two panels, the coefficient on HPI growth divergence is positive and statistically significant at the 1% level for both OLS and 2SLS estimates. While the OLS coefficient (0.012) in Column 1 of Table 19 is a little smaller than the one documented in Column 2 of Table 17 (0.015), a Wald test on the equality of the two regression coefficients suggests that the two coefficients are not statistically different from each other. When the dependent variable is income growth divergence or employment growth divergence, the coefficient on HPI growth divergence in Column 5 or 9 of Table 19 is the same or even larger than the corresponding coefficient documented in Table 17. These results show

Table 19: Potential hidden factors: banking integration and geographic proximity

This table examines alternative explanations and reports results based on both OLS (Panel A) and IV/2SLS (Panel B) regressions. The sample period is from 1988 to 2016 (except for indicated). In both panels, the dependent variables are denoted in the column head. Columns 1, 5, and 9 focus on the subsample of state pairs with banking integration measure of zero. Columns 2, 6, and 10 focus on the subsample of state pairs with banking integration measure of zero during the sample period of 1988-1993. Columns 3, 7, and 11 focus on the subsample of state pairs with above median capital city distance. Columns 4, 8, and 12 focus on the subsample of state pairs that do not share a common state boarder. HPI growth divergence is the absolute difference in Housing Price Index (HPI) growth rates of any state pair in year t. Log of GSP product and Log of population product are the logs of the products of two states' GSP and population, respectively. Difference in log GSP is the absolute difference in the logs of two states' GSP for any state pair in year t. All independent variables are measure in year t-1. Standard errors are clustered at the state-pair level. *, **, and *** denote statistically difference zero at the 10%, 5%, and 1% significant level, respectively.

Panel A. OLS results

	Bank integration measure=0		**Geographic proximity**		**Bank integration measure=0**		**Geographic proximity**		**Bank integration measure=0**		**Geographic proximity**	
	Full sample	**1988-1993**	**Large distance**	**Non-adjacent**	**Full sample**	**1988-1993**	**Large distance**	**Non-adjacent**	**Full sample**	**1988-1993**	**Large distance**	**Non-adjacent**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent variable:	**GSP growth divergence**				**Income growth divergence**				**Employment growth divergence**			
HPI growth divergence	0.012***	0.028***	0.020***	0.014***	0.017***	0.045***	0.021***	0.017***	0.008***	0.004**	0.008***	0.005***
	(0.004)	(0.008)	(0.005)	(0.003)	(0.003)	(0.006)	(0.004)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)
Bank integration			0.200	-1.323			-0.556	-0.890			-0.964**	-0.575*
			(1.407)	(0.864)			(1.202)	(0.722)			(0.409)	(0.338)
Log of GSP product	3.564***	21.824***	4.275***	3.629***	1.344***	13.378***	1.189***	1.586***	0.251	2.496***	0.266	0.172
	(0.337)	(2.159)	(0.399)	(0.315)	(0.211)	(1.845)	(0.256)	(0.195)	(0.162)	(0.449)	(0.180)	(0.145)
Log of population product	-3.358***	-19.575***	-3.607***	-3.142***	0.617	25.697***	1.733**	0.543	0.914**	-0.657	0.332	0.529
	(0.825)	(5.610)	(1.054)	(0.772)	(0.572)	(3.878)	(0.728)	(0.533)	(0.445)	(0.937)	(0.523)	(0.403)
Difference in log GSP	-0.363***	-0.514	-0.421***	-0.317***	-0.092	-2.691***	-0.087	-0.141	0.010	-0.359**	-0.001	0.002
	(0.137)	(1.110)	(0.150)	(0.119)	(0.108)	(0.706)	(0.104)	(0.091)	(0.078)	(0.163)	(0.082)	(0.064)
Difference in industry composition	18.506***	50.478**	17.632***	16.840***	9.597***	7.254*	1.131	8.245***	12.533***	-2.358	5.133*	9.899***
	(4.160)	(21.272)	(5.843)	(3.397)	(2.963)	(4.346)	(3.813)	(2.607)	(2.408)	(2.960)	(2.975)	(2.182)
State-Pair FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Time Trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28,120	5,520	18,502	33,901	21,680	5,520	14,025	25,718	21,680	5,520	14,025	25,718
Adj. R2	0.232	0.279	0.212	0.222	0.269	0.439	0.253	0.255	0.269	0.231	0.253	0.255

that the effect of HPI growth divergence on economic convergence in the low banking integration subsample is comparable to the effect of HPI growth divergence in the whole sample.

As discussed earlier, we use the data consolidated at the bank holding company (BHC) level to compute the banking integration measure. This approach makes the implicit assumption that commercial banks do not operate outside the borders of the state where they are located. This assumption is reasonable until the enactment of the Riegle-Neal Act of 1994, which allowed BHCs to consolidate activities in more than one states into a single commercial bank (e.g., Morgan et al., 2004). Thus, after

Table 19: (Cont.) Potential hidden factors: banking integration and geographic proximity

Panel B. 2SLS results

	Bank integration measure=0		Geographic proximity		Bank integration measure=0		Geographic proximity		Bank integration measure=0		Geographic proximity	
	Full sample	**1988-1993**	**Large distance**	**Non-adjacent**	**Full sample**	**1988-1993**	**Large distance**	**Non-adjacent**	**Full sample**	**1988-1993**	**Large distance**	**Non-adjacent**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent variable:	**GSP growth divergence**				**Income growth divergence**				**Employment growth divergence**			
HPI growth divergence	0.419***	0.597***	0.618**	0.532***	0.559***	0.418***	0.642**	0.753***	0.083	0.028	0.148	0.205**
	(0.128)	(0.207)	(0.243)	(0.176)	(0.137)	(0.136)	(0.255)	(0.211)	(0.058)	(0.091)	(0.096)	(0.082)
Bank integration			2.938	-0.566			-3.814*	-4.257**			-0.051	-0.375
			(2.048)	(1.568)			(2.239)	(1.838)			(0.875)	(0.735)
Log of GSP product	-0.215	5.602	0.236	-1.100	-0.541	2.368	-0.861	-1.385	0.299	-0.870	0.778*	-0.471
	(0.783)	(3.777)	(1.069)	(0.898)	(0.787)	(2.197)	(0.996)	(1.050)	(0.358)	(1.364)	(0.417)	(0.424)
Log of population product	-5.583**	-42.230***	-15.086***	-5.950**	4.983**	7.052	0.091	3.453	-2.962***	11.357*	-5.170***	-2.160**
	(2.406)	(14.657)	(4.259)	(2.384)	(2.510)	(9.663)	(3.605)	(2.623)	(1.084)	(6.269)	(1.427)	(1.065)
Difference in log GSP	-0.169	9.710***	0.071	0.060	-0.178	2.661	-0.181	-0.339	-0.009	-4.238***	-0.079	-0.047
	(0.282)	(2.842)	(0.348)	(0.246)	(0.276)	(1.890)	(0.303)	(0.274)	(0.123)	(1.292)	(0.128)	(0.111)
Difference in industry composition	22.675***	30.487	13.673	18.574***	11.583***	-42.246	0.051	9.872***	17.187***	-23.469	7.297*	14.828***
	(6.980)	(48.432)	(9.888)	(6.073)	(4.407)	(28.203)	(4.729)	(3.613)	(3.488)	(18.661)	(4.024)	(3.261)
State-Pair FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Time Trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,526	4,353	9,756	18,883	14,526	4,353	9,756	18,883	14,526	4,353	9,756	18,883

1994, the location data at the BHC level are less reflective of the actual locations of bank assets, which may introduce measurement errors to the Co-Herfindhal variable in the later period of our sample. To ensure that the bank consolidation started in 1994 does not affect our ndings, we redo the OLS and 2SLS regressions for a sample period prior to 1994, i.e., from 1988 to 1993. Results based on OLS (2SLS) regressions are reported in columns 2, 6, and 10 of Panel A (B) in Table 19. Again, the coefficient on HPI growth divergence is positive and statistically significant at the 1% level for all three dependent variables in both panels. Taken together, the results in the first two columns of Table 19 show that the effect of house price divergence on economic growth divergence remains very strong in the subsample of states that are likely to have very low bank integration, which does not support banking integration as a confounding factor behind our findings.

The second alternative explanation is that the states that are geographically close to each other can drive our results. Saiz (2010) suggests that geography is a key factor that influences house prices and economic development in the Unites States. States that are geographically close to each other are likely to have similar geographic endowments that may induce similar growth patterns in the housing market and the real economy. Using international data, Baxter and Kouparitsas (2005) find that geographic distance is important in explaining the business cycle co-movements across countries. Although state-pair fixed effects can account for the time-invariant factors across state-pairs including geographic distance, concerns about omitted variables may remain. For example, closely located states may share similarities in economic and social characteristics that can affect both the real economy and the housing market. These commonalities between the states could be changing over time as the states develop economically and socially. The fixed effects also may not fully control for the variations in the easiness of commute between the two states, which again could be changing over the years.

To rule out the neighboring states effects, we focus on state pairs that are relatively far from each other (above the median geographic distance of the sample). We collect information on state capital cities' latitudes and longitudes for 50 U.S. states plus Washington D.C., and employ the "Haversine" formula to calculate the great-circle distance between two points i.e., the shortest distance over the earths surface. If the omitted variables related geographic proximity drive our results, we should find weaker effect of HPI growth divergence on real economic growth divergence for the subsample of state pairs that are more distant from each other. Columns 3, 7, and 11 in Panel A (OLS) and B (2SLS) of Table 19 report the results for the large distance subsample. The coefficient on HPI growth divergence is positive and statistically significant at the 1% level in all columns in Panel A. Both coefficient magnitude and statistical significance are not any weaker than those of the whole sample. In Panel B, the coefficient on HPI growth divergence is positive and statistically significant at the 5% level for GSP growth divergence and income growth divergence and it is positive but not statistically significant at a conventional level for employment growth divergence. The weaker coefficient from the 2SLS estimation for employment growth divergence might be a result of smaller sample size and/or the higher sensitivity of this result to the endogeneity control.

One potential issue of using the geographic distances of capital cities is that capital cities in large states may have larger distance to capital cities in other states even if they share common borders. To mitigate this bias, we use an alternative measure that determines the geographic closeness of state pairs based on whether they are contiguous to each other (i.e., adjacent states). We then repeat our analysis in the state pairs that are non-adjacent. Results are presented in columns 4, 8, and 12 of Panel A (OLS) and B (2SLS) in Table 19. The coefficient on HPI growth divergence is positive for these non-adjacent state pairs, and is statistically significant at the 1% level in all columns except for column 12 in Panel B, which is significant at the 5% level. The magnitudes of both the OLS and 2SLS coefficients are comparable to those in Table 17 and 18. Taken together, results in Table 19 do not support the argument that the relations between HPI growth divergence and economic growth divergence measures are driven by geographic proximity.

2.4 Economic mechanism

2.4.1 The collateral channel

Results thus far support our hypothesis that real economic convergence follows housing market integration. In this section, we examine whether housing market integration affects real economic convergence through the collateral channel. The basic idea is that real estate properties are often used as collaterals for debt financing. Firms and households owning properties in integrated housing markets may experience correlated fluctuations in their debt capacity. We expect these correlated fluctuations in debt capacity to lead to correlated economic activity. Intuitively, in state pairs with integrated housing markets, increases in the property values allow borrowers in these states to borrow more and consequently, invest and hire more (Chaney et al., 2012;

Mian and Sufi, 2014; Corradin and Popov, 2015; Adelino et al., 2015; Schmalz et al 2017).

Formally, models of credit constraints where net worth is a measure of such constraints yield similar predictions (e.g., Bernanke and Gertler 1989; Kiyotaki and Moore 1997). For example, if the banking sector requires firms and households to have sufficient net worth as collateral for borrowing, an increase in collateral value leads to increase in net worth, which relaxes the credit constraints on the growth of economic activity. Extending this argument to housing market integration, when housing markets are more integrated across states, the co-movement in house prices is likely to generate correlated changes in collateral values, which in turn results in correlated shifts in credit constraints across states, leading to the convergence of economic growth.

Moreover, even in the absence of new debt issuance, the changes in the collateral values could affect the existing loan to value ratios. For example, the recent housing market crisis has substantially depreciated house values, which results in high loan to value ratios (even negative equity) for many household (e.g., Melzer, 2017). The high loan to value ratios create the classical debt overhang problem (Myers 1977). Melzer (2017) finds that debt overhang reduces homeowners incentives to invest in their property, even when they appear financially unconstrained. Donaldson et al. (2016) demonstrate theoretically how debt overhang may amplify unemployment by engaging levered households in risk-shifting by searching for jobs with high wages but low employment probabilities. Bernstein (2017) provides empirical evidence consistent with the predictions. Moreover, debt overhang may also lock in workers to their current locations, and reduce labor mobility and supply (Stein, 1995). Brown and Matsa (2017) find empirical evidence consistent with suboptimal job search patterns in depressed housing markets during the Great Recession. These papers collectively suggest that changes in collateral values could amplify economic downturn by reducing investment and employment.

If housing market integration influences economic convergence through the collateral channel, we would expect increased convergence in borrowing activities and loan structures when there is a convergence in collateral values between the states. We use two measures to capture a states loan structure. Real estate secured loans and home equity lines are two alternative ways of borrowing against house values. We construct one measure to capture the prevalence of real estate-secured loans in a state and another measure to capture the prevalence of the home equity line of credit (HELOC) in a state. The data on the amount of real estate-secured loans and the drawn HELOC are from the Call Reports.[7]

The first measure, $RE - securedLoans\%$, is the fraction of total real estate-secured loans issued in a state over total bank assets (or bank loans) in the state. The second measure, $HELOC\%$, is the drawn HELOC over total loans in the state. To measure the divergence of loan types across states, we calculate the absolute difference in these two measures between a state pair respectively. The absolute difference in $RE - securedLoans\%$ is the dependent variable in Column 1 and 2 and the absolute difference in $HELOC\%$ is the dependent variable in Column 3 and 4 of Panel A (OLS) and Panel B (2SLS) in Table 20. To support the collateral channel, we expect HPI growth divergence to increase the divergence in the proportion of real estate backed loans or HELOC between the states, i.e., a positive coefficient on the HPI growth divergence measure. The intuition is as follows: if state i experiences a growth in house prices while state j does not, then the divergence of house price growth in states i and j increases. Since there will be increases in real estate backed borrowing in state i because of higher collateral values, the gap in the proportion of

[7]To the best of our knowledge, no data exist on all HELOCs originated in the United States. We obtain HELOCs on banks' balance sheets from the Call Report but we do not have information on securitized HELOCs. Thus, the results on HELOCs should be interpreted with caution as we do not have the complete data on total HELOCs.

Table 20: The collateral channel

This table examines the collateral channel and reports OLS results in Panel A and 2SLS results in Panel B. The sample period is from 1988 to 2016. In both panels, the dependent variable in columns 1-2 is RE-secured loans% divergence, defined as the absolute difference in the fraction of total real estate-secured loans issued in a state over total bank assets in the state; the dependent variable in columns 3-4 is the absolute difference in the fraction of HELOC over total loans between two states. HPI growth divergence is the absolute difference in Housing Price Index (HPI) growth rates of any state pair in year t. Log of GSP product and Log of population product are the logs of the products of two states GSP and population, respectively. Difference in log GSP is the absolute difference in the logs of two states GSP for any state pair in year t. All independent variables are measured in year t-1. Standard errors are clustered at the state-pair level. *, **, and *** denote statistically difference zero at the 10%, 5%, and 1% significant level, respectively.

	OLS results				2SLS results			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	RE-secured loans% (assets) divergence		**HELOC/Gross loans Divergence**		**RE-secured loans% (assets) divergence**		**HELOC/Gross loans Divergence**	
HPI growth divergence	0.033**	0.034**	0.013***	0.013***	1.607**	1.658**	0.650***	0.644**
	(0.013)	(0.013)	(0.004)	(0.004)	(0.677)	(0.689)	(0.252)	(0.254)
Bank integration		-0.919		1.840		-4.251		5.155**
		(3.725)		(1.235)		(5.063)		(2.116)
Log of GSP product		2.936**		1.469***		-1.892		4.007***
		(1.298)		(0.381)		(3.333)		(1.223)
Log of population product		2.069		-2.950***		39.876***		0.926
		(5.157)		(1.031)		(8.294)		(2.642)
Difference in log GSP		1.314		0.593***		-0.864		0.844**
		(0.843)		(0.229)		(1.011)		(0.370)
Difference in industry composition		-68.185***		-10.975*		-84.922***		-8.987
		(19.969)		(5.610)		(28.951)		(8.315)
State-Pair FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Time Trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	33,258	33,258	33,213	33,213	20,690	20,690	20,690	20,690
Adj.R2	0.554	0.555	0.503	0.504				

real estate secured loans or HELOC for states i and j will widen as well. Supporting this prediction, the coefficient on HPI growth divergence is positive and statistically significant for both OLS and 2SLS estimations in Table 20. These results show that housing market integration increases the convergence in loan structures across states, which supports the collateral channel as a mechanism that transfers changes in house prices to the real economy.

2.4.2 Alternative channels

We consider two alternative channels through which housing market integration may influence real economy synchronization. First, the results may be mechanically driven by the boom and bust of the real estate industry itself, especially when the real estate industry accounts for a large proportion of the economy in a state. If this concern is valid, the effect of housing growth divergence is not on overall economy and is on real estate industry instead, and the removal of real estate industry in computing economic growth can result in insignificant results. We test this hypothesis by excluding real estate industry and compute the output (i.e., GSP) growth. Column 1 in Table 21 reports the result. The dependent variable is the absolute difference in real GSP growth with real estate industry excluded for states i and j in year t. We continue to account for the gravity controls and the difference in log GSP per capita, as well as state-pair fixed effects, year fixed effects and state-time trend. The coefficient on housing growth divergence remains positive and significant. Interestingly, the magnitude of the coefficient (0.693) is even slightly larger as opposed to the coefficient in column 4 in Table 17 Panel A (0.654). This result implies that our results are not driven by the mechanical issue of real estate effects *perse*.

Another alternative channel is changes in local demand. Since increases in real estate prices may improve the perception of firms and individuals on their future wealth, they may increase their current consumption level and drive up local demand for goods (Campbell and Cocco, 2007) and employment in non-tradable industries (Mian and Sufi, 2014). Based on these arguments, one may have the following conjecture: the convergence of housing market growths between two states leads to converging demand for local services (e.g., local construction, retail trade, or personal and business services), and these converging local demand may create co-movements in the growth of state economies. If the relation between housing market integration and real economic convergence is mainly driven by this local demand channel, instead of the collateral channel, we should find weaker results when we remove from our sample non-tradable industries that are more sensitive to local demands. We follow Mian and Sufi (2014) to define non-tradable industries and exclude them from the estimation

Table 21: Alternative channel explanations: real estate industry and local demand

This table examines alternative channel explanations and reports the OLS (columns 1 to 4) and 2SLS results (columns 5 to 8). The sample period is from 1988 to 2016. The dependent variable is GSP growth divergence, i.e., the absolute difference in GSP growth rates between any state-pair in year t for various subsamples: Columns 1 and 5 exclude the real estate sector; columns 2 and 6 focus on the GSP growth after excluding non-tradable sectors; columns 3 and 7exclude construction industry; columns 4 and 8 exclude both non-tradable and construction sectors. We follow Mian and Sufi (2014) to identify the non-tradable sectors. HPI growth divergence is the absolute difference in Housing Price Index (HPI) growth rates of any state pair in year t. Log of GSP product and Log of population product are the logs of the products of two states GSP and population, respectively. Difference in log GSP is the absolute difference in the logs of two states GSP for any state pair in year t. All independent variables are measured in year t-1. Standard errors are clustered at the state-pair level. *, **, and *** denote statistically difference zero at the 10%, 5%, and 1% significant level, respectively.

	OLS Results				2SLS Results			
		Local demand driving the results				Local demand driving the results		
	Exclude RE	**Exclude non-trad.**	**Exclude constr.**	**Only Manuf.**	**Exclude RE**	**Exclude non-trad.**	**Exclude constr.**	**Only Manuf.**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
HPI growth divergence	0.007*	0.013***	0.011***	0.051***	0.642***	0.503**	0.653***	3.685***
	(0.003)	(0.003)	(0.003)	(0.013)	(0.224)	(0.202)	(0.217)	(1.190)
Bank integration	-1.033	-1.540*	-1.547**	0.771	-0.566	-0.246	-0.628	-5.150
	(0.799)	(0.825)	(0.725)	(2.611)	(1.598)	(1.373)	(1.590)	(8.333)
Log of GSP product	3.590***	3.546***	3.434***	-1.071	-2.075**	-1.573*	-2.103**	-24.608***
	(0.320)	(0.330)	(0.300)	(0.991)	(1.042)	(0.935)	(1.007)	(5.399)
Log of population product	-3.301***	-2.615***	-2.365***	2.392	-3.002	-3.762*	-2.112	35.736***
	(0.786)	(0.813)	(0.728)	(2.234)	(2.527)	(2.266)	(2.467)	(11.972)
Difference in log GSP	-0.265**	-0.337***	-0.371***	-0.781**	0.113	0.042	-0.007	-0.723
	(0.122)	(0.123)	(0.113)	(0.388)	(0.271)	(0.245)	(0.265)	(1.262)
Difference in industry composition	18.704***	16.905***	18.253***	21.362***	20.985***	16.669***	20.825***	17.536
	(3.366)	(3.318)	(3.271)	(7.849)	(6.450)	(5.796)	(6.509)	(29.255)
State-Pair FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Time Trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	36,975	36,975	36,975	36,975	20,690	20,690	20,690	20,690
Adj. R2	0.220	0.219	0.222	0.238				

of GSP growth divergence.[8] Results based on this alternative real economic growth divergence measure is presented in Column 2 and 6 of Table 21. In Column 3 and 7, we present results after excluding the construction industry, which is also highly related to the local demand. In Column 4 and 8, we present results after excluding both non-tradable and construction industries. The coefficient on HPI growth divergence is positive and statistically significant at the 1% level in all six columns for

[8]Specifically, our classification of non-tradable sectors is obtained from the Online Appendix Table A2 of Mian and Sufi (2014). Non-tradable sectors include retail trade, accommodation and food services, and hospitals and residential care facilities. We download the industry-level output data from the BEA and calculate annual growth rates after excluding non-tradable sectors.

both OLS and 2SLS estimates. These results show that the impact of HPI growth divergence on economic divergence remains strong after we remove industries that are more sensitive to changes in local demand, which suggests that changes in local demand is unlikely to be the main channel through which housing market integration influences real economic convergence in the remaining industries.[9]

2.5 Additional robustness checks

In this section, we show that our results are robust to a few additional robustness checks. In the first set of robustness checks, we consider a few alternative measures of the dependent and independent variables. In the second set of robustness checks, we consider a few alternative sample periods. In the last set of robustness checks, we use an alternative instrumental variable and redo our analysis at the metropolitan statistical area (MSA) level. For all robustness checks reported, we only report the coefficients of housing market integration measures in Table 22 to preserve space, but all regressions include control variables and fixed effects as in Table 17. Only OLS results are report for the first two sets of robustness checks, but we note that the untabluated results from the 2SLS estimation are very comparable to those reported in Table 17.

We first show that our results are robust to alternative integration measures. As discussed in Section 2, we constructed four housing market integration measures: (i) the absolute difference in HPI growth rates between two states, (ii) the correlation of quarterly HPI growth rates between a state pair over a rolling 5-year (20-quarter) window, (iii) the covariance of quarterly HPI growth rates between a state pair over a rolling 5-year (20-quarter) window, and (iv) the absolute difference in HPI growth residuals between two states. We also construct two sets of real economic convergence

[9]Our analysis here cannot rule out the possibility that changes in local demand may be a motive or an outcome of the collateral channel. Increases in local demand may be a motivation for local firms or households to borrow and invest. As an outcome of the borrowing and investing activities, local economy may be simulated and demand could increase.

Table 22: Additional robustness checks

This table presents OLS results for various robustness checks. Panel A reports alternative integration measures. The dependent variables are GSP growth residual divergence in columns 1 and 2 and Income growth residual divergence in columns 3 and 4, and Employment growth residual divergence in columns 5 and 6. These variables are the absolute difference in the residuals of real growth rates between any state-pair in year t, computed using GSP, income, and total employment growth rates, respectively. The residuals are obtained from regressing the real growth rate on state and year fixed effects. 5-yr HPI correlation (covariance) is the pairwise correlation (covariance) of real estate price growth across U.S. states computed over a five-year-backward rolling window with quarterly data. HPI Growth residual divergence are the absolute difference in the residuals of Housing Price Index (HPI) growth rates between any state-pair in year t. The residuals are obtained from regressing the HPI growth rate on state and year fixed effects. Panel B reports an alternative sample period of 1975-2016. Panel C reports an alternative sample period of 1995-2016. Panel D reports the MSA-level results during the sample period of 2001-2016. In all panels, we only report the coefficient on HPI growth divergence to preserve space. HPI growth divergence is the absolute difference in Housing Price Index (HPI) growth rates of any state pair in year t. When noted, the regressions include the four control variables as in prior tables. Standard errors are clustered at the state-pair level. *, **, and *** denote statistically difference zero at the 10%, 5%, and 1% significant level, respectively.

Panel A. Alternative integration measures (36,975 obs.)						
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	**GSP growth divergence**		**Income growth divergence**		**Employment growth divergence**	
5-yr HPI correlation	-0.219***	-0.201***	-0.236***	-0.234***	-0.102***	-0.102***
	(0.051)	(0.049)	(0.041)	(0.040)	(0.027)	(0.027)
Adj.R2	0.214	0.222	0.252	0.256	0.200	0.201
Dependent variable:	**GSP growth divergence**		**Income growth divergence**		**Employment growth divergence**	
5-yr HPI covariance	-0.064***	-0.059***	-0.035***	-0.032***	-0.037***	-0.036***
	(0.012)	(0.012)	(0.010)	(0.010)	(0.007)	(0.007)
Adj.R2	0.214	0.222	0.251	0.255	0.200	0.201
Dependent variable:	**GSP growth residual divergence**		**Income growth residual divergence**		**Employment growth residual divergence**	
HPI growth residual	0.017***	0.016***	0.019***	0.018***	0.007***	0.007***
divergence	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
Adj.R2	0.212	0.220	0.255	0.262	0.200	0.201
Panel B. Alternative Sample 1975-2016						
	GSP growth divergence		**Income growth divergence**		**Employment growth divergence**	
HPI growth divergence	0.005**	0.004**	0.008***	0.010***	0.005***	0.004***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
Observations	49,725	49,725	52,275	49,725	51,000	49,725
Adj.R2	0.224	0.237	0.279	0.276	0.185	0.189
Panel C. Alternative Sample 1995-2016						
	GSP growth divergence		**Income growth divergence**		**Employment growth divergence**	
HPI growth divergence	0.020***	0.018***	0.008**	0.008**	0.006***	0.006**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)
Observations	28,050	28,050	28,050	28,050	28,050	28,050
Adj.R2	0.252	0.254	0.260	0.263	0.196	0.202
Control Variables		Yes		Yes		Yes
State-Pair FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State Time Trends	Yes	Yes	Yes	Yes	Yes	Yes

Table 22: (Cont.) Additional robustness checks

Panel D. MSA-level results						
OLS	(1)	(2)	(3)	(4)	(5)	(6)
HPI growth divergence	0.014***	0.016***	0.019***	0.008***	0.009***	0.010***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.001)	(0.001)
Log of GSP product		0.867***		0.476**		-0.319**
		(0.276)		(0.225)		(0.144)
Log of population product		-6.981***		-4.883***		2.199***
		(0.676)		(0.646)		(0.524)
Difference in log GSP		-0.458**		0.854***		0.329***
		(0.198)		(0.167)		(0.108)
State-Pair FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State Time Trends	Yes	Yes	Yes	Yes	Yes	Yes
Observations	58,740	58,740	62,656	58,740	62,656	58,740
R-squared	0.245	0.247	0.343	0.351	0.374	0.378
r2_a	0.188	0.190	0.296	0.303	0.331	0.332
IV	(1)	(2)	(3)	(4)	(5)	(6)
HPI growth divergence	0.931***	0.993***	0.098	0.134	0.316***	0.263***
	(0.190)	(0.205)	(0.106)	(0.101)	(0.078)	(0.066)
Log of GSP product		-3.984***		-0.147		-1.574***
		(1.109)		(0.555)		(0.360)
Log of population product		-23.561***		-7.012***		-2.089
		(4.038)		(1.787)		(1.373)
Difference in log GSP		0.826*		1.019***		0.661***
		(0.497)		(0.210)		(0.162)
State-Pair FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State Time Trends	Yes	Yes	Yes	Yes	Yes	Yes
Observations	58,740	58,740	62,656	58,740	62,656	58,740

measures: (i) the absolute difference in GSP, income, or employment growth rates between a state pair, and (ii) the absolute difference in GSP, income, or employment growth residuals between a state pair. Results in prior sections are based on the respective first measure for either housing market integration or economic convergence, i.e., the absolute difference in growth rates between two states. We show regression results based on these alternative integration measures in Panel A of Table 22. The upper part of Panel A presents results based on the 5-year correlation of HPI growth rates between a state pair, the middle part presents results based on the 5-year covariance of HPI growth rates between a state pair, and the lower part present results based on the absolute difference of growth residuals between a state pair. The coefficients on the HPI correlation and covariance measures are negative and the coefficients on the growth residual based housing market divergence are positive. All coefficients are statistically significant at the 1% level. These findings are consistent with our hypothesis that housing market integration (higher correlation/covariance or lower HPI residual divergence) decreases economic divergence.

Next, we consider the robustness of our results for alternative sample periods. The sample period in baseline analyses is from 1988 to 2016. As a robustness check, we start our main sample from 1995 to mitigate the influence of bank deregulation on our results because the cross-state bank deregulations start in 1975 and are completed in 1994. We also repeat our analysis in Table 17 for a longer sample period: 1978 to 2016. The GSP data from 1978 to 1987 are backed out from the Quantity Indexes data for Real GDP by state from the BEA. As reported in Panel B and C of Table 22, all our results in Table 17 hold in these two alternative sample periods. Specifically, the coefficient on HPI growth divergence is positive and statistically significant at the 5% level or better in all specifications. These results suggest that the effect of housing market integration on real economic convergence is not just an artifact of the particular sample period we use, 1988 to 2016.

Lastly, we use the MSA-level elasticity of land supply developed by Saiz (2010) as an alternative instrument to identify exogenous variations in changes in house prices. Saiz (2010) uses satellite generated data on terrain elevation and presence of water bodies to estimate the elasticity of land supply in the U.S. The elasticity of land supply has been used as an instrument for house prices in many studies (e.g., Mian and Sufi, 2011, 2014; Chaney et al., 2012; Charles, Hurst, and Notowidigdo, 2012; Robb and Robinson, 2013; Adelino et al., 2015; Loutskina and Strahan 2015). Following the ideas in these papers, the alternative instrument we use for house price divergence is the absolute difference in land supply elasticity between two MSAs interacted with the change in the aggregate interest rate (IR) for MSAs i and j in year t.

We first discuss the relevance of this instrument. When interest rates decrease, the demand for real estate increases. If the local supply of land is very elastic, the increased demand will likely translate into more construction (more quantity) rather than higher land prices. If the supply of land is very inelastic on the other hand, the increased demand will likely translate into higher prices rather than more construction. If two MSAs differ in land supply elasticity, changes in aggregate interest rates will likely result in different house prices in these two areas (i.e., the absolute difference in HPI growth rates increases). Thus, the interaction between the differences in land supply elasticity and changes in interest rate affects the divergence in house prices, satisfying the relevance requirement of an instrument.

The exclusion restriction of the instrumental variable requires that the elasticity of the housing supply affects real economic activities only through its effect on house prices. This exclusion restriction has been assumed in the studies that utilize this instrument because the geographic location and characteristics of an MSA is considered exogenous to its local economic and social development. However, as shown in Saiz (2010), the land supply elasticity measure is a function of both physical and regulatory constraints. These constraints may directly affect the activities in both the housing market and the real economy, which may render the instrument non-exogenous to changes in house prices. Moreover, Davidoff (2013) finds that the cross-sectional price variation in U.S. housing markets during the 2000s housing market cycle does not relate to the land supply elasticity, which casts doubt on the relevance of this instrument to changes in house prices. Nevertheless, to be consistent with the literature, we use the land supply elasticity to construct an alternative instrumental variable to examine if our results hold with this alternative IV. Because of the endogeneity concern, however, these results should be interpreted with caution.

The regression results based on this alternative IV are reported in Panel D of Table 22. The housing supply elasticity measure in Saiz (2010) is available for 95 MSAs. We are able to match 89 of these 95 MSAs with MSA-level output and income data from the BEA and MSA-level employment data from the Bureau of Labor Statistics (BLS). The MSA-level output data are only available from 2001 onwards. As a result, the sample for this alternative IV has 3,916 MSA pairs and 58,740 MSA pair year observations for the period of 2001 to 2016. We report the OLS results in the upper half of Panel D and the second stage IV estimation results in the lower half of Panel D. The coefficient of HPI growth divergence is positive and significant at the 1% level across all the OLS specifications. For the 2SLS estimations, the coefficient on HPI growth divergence is positive and significant at the 1% level for GDP growth divergence and employment growth divergence. For income growth divergence, the coefficient is positive but not statistically significant. Collectively, results in Table 22 confirm the robustness of our main finding that housing market integration increases economic convergence across states.

2.6 Concluding Remarks

Motivated by the growing trend of housing market integration, our paper examines whether and how housing market integration influences real economy synchronization between U.S. states. We find that housing market integration increases economic synchronization. Using an instrumental variable that is orthogonal to local economic conditions but is highly related to housing market integration, we show that influence of housing market integration on economic synchronization is causal. This influence of housing market on economy is not subsumed by banking integration or geographic proximity between the states. Supporting the collateral channel as the main mechanism through which housing market integration influences economic synchronization, we find that the influence of housing market concentrates in the collateral intensive industries and housing market integration increases the convergence of loan structure across states. Theory and empirical evidence show that real estate collateral can amplify production shocks and thus exaggerate business cycle volatility (e.g., [20]; [39]). Our paper suggests that the convergence of real estate growth cycle creates common shocks in collateral values, which increases the synchronization of states' business cycles.

Both the global economy and the U.S. domestic economy have become increasingly integrated in the past several decades. To some extent, the nexus of these market integrations characterizes the modern economy. The literature has documented the importance of capital market integration, in particular, banking integration, to economic synchronization (e.g., [9], [145]). Our results point to the contribution of the real estate market integration to economic convergence. More studies are needed to understand the interactions of various types of market integrations.

CHAPTER III

GLOBAL DIVERSIFICATION WITH LOCAL STOCKS: A ROAD LESS TRAVELED

3.1 Introduction

Since the classic works of [91], [123], and [161], numerous studies have documented the significant gains from international portfolio diversification, using various sample markets over different sample periods. The rising awareness among investors of potentially large benefits from international diversification, together with the steady dismantling of barriers to cross-border capital flows, led to remarkable growth of international portfolio investments. In recent years, however, researchers increasingly found that the gains from international diversification, within the universe of developed stock markets at least, have become largely insignificant (e.g., [63], [69], [41], [42], and [48]). This is likely due to the increased correlations and also the convergent risk-return attributes among the developed markets, reflecting the advanced global integration of these markets. In his pioneering work, [161] stated: "Several authors have shown that movements in stock prices in different countries are almost uncorrelated: Changes in price on the Paris Bourse appear independent of stock price fluctuations on the London exchange and so on." During our study period of 1995-2014, by comparison, the monthly return correlation between the two European stock market indices has fluctuated at around 0.89 in U.S. dollar terms. Apparently, the correlations between stock markets rose rather dramatically during the intervening years, largely eliminating room for gainful diversification.

In an effort to explore new ways of capturing benefits from international diversification, various studies have documented that investors may still gain significantly if they diversify into emerging or frontier markets that are obviously much less integrated globally than developed markets (e.g., [67], [93], [65], [63], [17], [41], and [19]). Investments in emerging and frontier markets, however, are often hampered by poor governance, political risks, lack of information, foreign exchange restrictions, and other barriers. In this paper, we propose another way of capturing benefits from international diversification within the familiar confines of developed markets, i.e., using "local" stocks of developed markets that are least driven by the common global factors.

Specifically, in this paper, we (i) estimate the degree of global financial integration at the firm-level to identify "local" stocks, in contrast to the prevailing practice of measuring the global integration mostly at the country-level, and (ii) utilize the estimated firm-level integration measures and its distributions for the purpose of optimal international portfolio diversification. In doing so, we estimate R-squares, our measure of global integration, from regressions of weekly individual stock returns (in dollars) on common global factors for a sample of about 51,000 individual firms from nine developed countries over our whole sample period, 1995-2014. We identify the global factors using the principal components extracted from nine country stock market indices, ten industry indices, and nine style indices (large vs. small and value vs. growth). Recognizing that stock returns may be driven by industry, style, as well as country attributes, all three sets of indices are utilized in identifying the global factors, not just the market indices as has usually been done in the literature. We otherwise closely follow the R-square method for measuring global financial integration proposed by [151].

Our findings regarding the R-squares show: First, the adjusted R-squares estimated for our pooled sample of international stocks are very widely distributed with the mean of 0.193 and standard deviation of 0.214. This implies that the degree of global integration varies greatly across individual firms, generating nearly a continuum of individual stocks distributed across the scale of R-squares. In fact, the adjusted R-square ranges from -0.506 to 0.930 across our international sample firms, with a fairly low median, 0.166. This stark heterogeneity in integration at the firm level is observed in each of our sample countries as well. Second, our ANOVA analysis indicates that the firm-level integration measure is significantly affected by each of the three categories of firm attributes tested - country, industry, and style. For instance, domicile of a firm in Japan (Germany) has a significantly positive (negative) effect on the firm's R-square, while a firm's classification as health care (energy) has a negative (positive) effect on its R-square. As can be expected, large-(small-) cap classification of a firm has a positive (negative) effect on the R-square, across value-growth spectrum. Overall, style attribute has the greatest (absolute) effect on the firm-level integration, followed by country and industry attributes. The integration effects of the three attributes are time-varying—on average, industry attribute has the most stable effect, albeit the weakest, while country attribute has the most volatile effect.

Our prior findings showing the strong heterogeneity in global integration at the firm level have immediate implications for international portfolio diversification: In principle, investors should be able to (i) minimize the portfolio risk by diversifying their portfolios using international pool of local stocks whose returns are least driven by the common global factors and also (ii) enhance the mean-variance efficiency of investment portfolios by optimally holding those local stocks.

We closely follow [161]'s procedure to examine the first implication. Specifically, we construct equally weighted portfolios with the varying numbers of stocks, ranging from 1 to 50 stocks, and compute the portfolio variance using weekly returns. To compute the variance of the portfolio with a particular number of stocks, we randomly pick stocks and compute the variance. This procedure is repeated 5,000 times. We then compute the average variance based on such simulations. For comparison purpose, we randomly pick stocks from three separate pools of stocks, i.e., local stocks, global stocks, both from all sample countries, and U.S. domestic stocks. Local (global) stocks are those classified into the bottom (top) decile portfolio sorted on R-squares. The simulation results show that on average, the variance of a fully diversified portfolio comprising local, global, and U.S. stocks is, respectively, about 6.3%, 22.3%, and 13.1% of the average variance of individual stocks. This implies that local stocks are far more effective in reducing the portfolio risk compared with either global or U.S. stocks. It is also noteworthy that the gains from international risk diversification with local stocks remain robust during the recent crisis years, such as 2000 (dotcom bubble burst) and 2008-2012 (U.S. subprime mortgage crisis and European sovereign debt crisis).[1] Furthermore, using 25 portfolios more finely sorted on R-squares, we show that the higher R-square of the portfolio is, the higher is the un-diversifiable (systematic) risk of the portfolio. Previous studies (e.g., [110] and [16]), however, show that most investors actually tend to tilt toward holding stocks with global, rather than local, attributes.

To effectively exploit the heterogeneity in global integration among individual stocks and enhance the mean-variance efficiency of the portfolio, which is the second implication of our earlier findings, we let investors hold "local portfolios" optimally in conjunction with country stock market indices. To implement this strategy, we systematically identify 'local' stocks, as explained previously, and construct the "local portfolio" comprising only those stocks classified into the last decile in terms of R-squares. Local portfolio is constructed for each country, industry, and style. Investors then may optimally allocate their funds across local portfolios and country market indices.

[1] For instance, in 2008 when the global financial crisis started by the U.S. subprime mortgage crisis was at its height, the variance of weekly percentage returns was 9.51 (33.67) for the fully diversified 'local' ('global') stock portfolio. Refer to Figure 3B for further details.

When investors optimize their portfolio choice only over stock market indices, the gains from international diversification as measured by the increase in the Sharpe ratio relative to the U.S. stock market index turn out to be insignificant, with or without short sales, which is consistent with the previous findings (e.g., [52]). However, once stock market indices are augmented by country local portfolios from the same set of countries, the resulting optimal portfolio has a monthly Sharpe ratio of 0.381 (0.247) with (without) short sales over the holding period 1995-2014, which is compared with a Sharpe ratio of 0.236 (0.159) for the optimal portfolio comprising stock market indices only, with (without) short sales. The test proposed by Gibbons, Ross, Shanken (GRS) shows that the increase in the Sharpe ratio is significant at the 5 (1) percent level with (without) short sales. When stock market indices are augmented with industry or style local portfolios, rather than country local portfolios, the Sharpe ratio increases a bit more, probably reflecting some additional gains from diversifying across different dimensions. Furthermore, when investors simultaneously optimize over stock market indices plus all three sets of local portfolios constructed along country, industry, and style dimensions, the Sharpe ratio rises sharply to 0.723 (0.303) with (without) short sales. Increases in the Sharpe ratio are significant at the 1 percent level. By comparison, the Sharpe ratio of the U.S. market index is 0.152 over the same holding period. The preceding result suggests that local portfolios organized along country, industry, and style lines are not redundant, but they rather may complement each other to further span the mean-variance space. Results from our portfolio analysis show that investors can still benefit greatly from international diversification without leaving the familiar environments of developed markets with generally better governance and less currency and political risks than the more venturesome markets at the far corners of the world.

Our robustness checks confirm that the analyses using [72] three-factor, [28] four-factor, or [73] five-factor models, in lieu of the Pukthuanthong-Roll method, generate

(i) very similar patterns of heterogeneity in global financial integration measures across individual firms and (ii) significant gains from international diversification with the local portfolios constructed with R-squares that are computed based on the Fama-French-Carhart global factors. To check if our main findings pertaining to the portfolio analysis are also robust to the use of alternative base currencies, apart from the U.S. dollar, we replicate the portfolio analysis using each of the eight currencies matching our international sample countries as the base currency. We find that most of the major findings from using the U.S. dollar as the base currency remain robust to the use of alternative base currencies. Particularly, in case investors optimize their portfolio selection using all three types of local portfolios, GRS tests indicate that the increase in the Sharpe ratio relative to the benchmark case of optimization with country market indices is statistically significant at the 5% level or better, with or without short sales, for every alternative base currency tested, without exception.

To sum up, our paper contributes to the long line of literature on international portfolio diversification by documenting the following two main points: (i) Individual stocks differ greatly in the degree of global integration and there are plenty of highly local stocks that are minimally exposed to the common global factors in developed markets, and (ii) despite the evident globalization of stock markets in recent decades, investors can still benefit greatly by systematically identifying these local stocks and holding them optimally, within the familiar confines of developed markets. Our paper thus sheds rather positive light on the value of developed markets for investors' global diversification. By taking the granular, bottom-up approach to global asset allocation, we show that investors can span the mean-variance space much beyond what's feasible with stock markets indices that are disproportionately affected by global integration. Thus, inferences of the gains from international diversification solely from stock market indices, the usual practice among practitioners and academics, are likely to significantly understate the true magnitude of the benefits that world stock markets can provide. From our findings, we can also derive a practical, albeit a little counterintuitive, advice that should be beneficial for investors: Take a road less traveled by holding local stocks for global diversification, rather than globally oriented stocks that many investors are known to hold for their global investments. At the macro level, local stocks can play an important role of countervailing against the rising, pervasive effect of the common global factors on the behavior of asset returns that accompanies financial integration. This would help to keep global risk sharing effective.

The rest of our paper is organized as follows. Section 2 describes the data and sample selection. Section 3 measures global financial integration at the firm level and examines the effects of country, industry, and style attributes on the degree of firm-level integration. Section 4 estimates the effectiveness of international local stocks for portfolio risk diversification based on simulations, while Section 5 estimates the mean-variance gains from international diversification using local portfolios. Section 6 discusses robustness checks. Lastly, Section 7 provides concluding remarks.

3.2 Data and Sample Selection

We utilize the data on individual stocks and stock market indices from nine developed countries of Australia, Canada, France, Germany, Hong Kong, Japan, Switzerland, the U.K., and the U.S. during the period of 1995-2014. It is noted that during this period, there existed relatively few formal barriers to international investment in our sample countries. The firm-level data are from the Center for Research in Security Prices (CRSP) and COMPUSTAT for the U.S and from Thomson Financial's Datastream for the rest of sample countries. Specifically, we use U.S. dollar-based weekly and monthly returns of all available individual stocks in the nine sample countries.[2] In addition, we obtain the one-year U.S. Treasury yield from Federal Reserve Economic Data and use it as a proxy for the risk-free interest rate.

We apply certain filters to select only common stocks that are traded in their home countries. For U.S. stocks from CRSP, we require that the share code (SHRCD) is equal to 10 or 11 to keep only ordinary common shares and that the exchange code (EXCHCD) is equal to 1, 2, or 3 to keep only the stocks traded on NYSE, AMEX, or NASDAQ. For non-U.S. stocks from Datastream, we use the following filters:[3] (i) We require that the type of instruments is classified as equity (TYPE=EQ); (ii) we exclude stocks with firm names (NAME) indicating that they are not common stocks such as preferred stocks or warrants; (iii) we filter out stocks that are traded in foreign countries by restricting the geography groups (GEOG) to be their home countries; (iv) we eliminate stocks with industry names (INDM) and codes (INDC6) for investment vehicles, such as mutual funds, unit trusts, and other forms; (v) when a stock has multiple classes, we select the primary class by requiring the major security flag (MAJOR) to be 1; (vi) we also apply some country-specific filters to exclude non-equity stocks.[4] Also, to eliminate data errors in Datastream, we apply the following filters:[5] (i) For weekly or monthly returns, if both conditions of a) r_t or $r_{t-1} > 100\%$ and b) $(1+r_{t-1})(1+r_t)-1 < 20\%$ are met, then both r_t and r_{t-1} are set to missing; (ii) any weekly or monthly return greater than 200% is treated as missing; (iii) for each pair of country and year, we construct the distribution of individual stock returns and treat as missing the weekly or monthly returns that fall out of the 0.1% and 99.9% quantile range.

[2]For U.S. firms, the weekly stock returns are calculated by compounding the daily stock returns obtained from CRSP Daily over the trading days in the corresponding week; for non-U.S. stocks, the weekly returns are obtained from Datastream.

[3]Our filters are similar to those employed by [90] and [111].

[4]The list of keywords in firm names as filters is provided in Panel A of Table A2. The list of keywords in industry names and codes as filters is provided in Panel B of Table A2. The list of country-specific filtering keywords is provided in Panel C of Table A2.

[5]Our empirical results are robust to other thresholds within a reasonable range.

Table 23: Descriptive Statistics

This table describes the equity markets of our nine sample countries: Australia, Canada, France, Germany, Hong Kong, Japan, Switzerland, U.K. and U.S. All reported numbers are the annual averages over our sample period 1995-2014. Panel A reports the average of (i) the size of stock markets in terms of the number as well as the aggregate market capitalization of our filtered sample firms (first two columns) and (ii) the summary statistics of the cross-sectional distribution of market capitalization and book-to-market ratio of individual stocks for each of the nine sample countries. Panel B summarizes the industry distribution in each of our nine sample countries. After we classify individual stocks into 10 industries, determined by Global Industry Classification Standard (GICS) 10 Sector codes – energy, materials, industrials, consumer discretionary, consumer staples, health care, financials, information technology, telecommunication services, and utilities –, we compute (i) count-based industry distribution: the ratio of the number of firms in each industry to the total number of firms in that country and (ii) value-based industry distribution: the ratio of the total market value of firms in each industry to the total market value of that country. The last column reports the industry Herfindahl-Hirschman index (HHI), which is computed by summing over the squared count-(value-)based industry shares in each country.

Panel A. Number of firms, market value, firm size and book-to-market ratio

	No. of Sample Firms	Aggregate Market Size ($B)	Firm Size ($M)				Book-to-Market Ratio			
			Mean	1st Quartile	Median	3rd Quartile	Mean	1st Quartile	Median	3rd Quartile
Australia	1,107	709.71	618.01	8.52	29.18	150.63	0.83	0.29	0.58	1.05
Canada	697	1,597.93	2,079.44	44.14	225.91	1,148.60	0.79	0.31	0.56	0.97
France	689	1,382.19	2,005.73	24.30	92.88	499.93	0.87	0.36	0.65	1.10
Germany	724	1,240.07	1,876.55	21.72	83.39	425.75	0.91	0.34	0.63	1.14
Hong Kong	790	968.67	1,138.68	39.25	104.48	377.86	1.39	0.45	0.98	1.91
Japan	3,356	3,488.22	1,101.72	56.49	149.79	507.80	1.25	0.64	1.07	1.66
Switzerland	225	850.78	3,817.12	124.86	387.02	1,301.15	1.17	0.50	0.87	1.44
U.K.	1,224	2,429.55	1,969.19	27.62	108.01	571.24	0.72	0.22	0.47	0.94
U.S.	5,316	12,701.24	2,668.82	65.85	259.12	1,100.96	0.68	0.36	0.59	0.88
All Countries	14,127	25,368.35	1,664.84	34.23	129.91	598.82	0.98	0.36	0.68	1.18

After applying the filters above, we obtain a total of 51,118 individual stocks from the nine sample countries, or 14,127 individual stocks per year on average. Table 23 describes our sample data. All reported numbers are the annual averages over our sample period 1995-2014. Panel A of Table 23 reports the average of (i) the size of stock markets in terms of the number as well as the aggregate market capitalization of our filtered sample firms (first two columns) and (ii) the summary statistics of the cross-sectional distributions of market capitalization and book-to-market ratio of individual stocks in each of the nine countries. In our sample, the average number of common stocks in the U.S. (5,316) is more than one third of that from all nine

Table 23: (Cont.) Descriptive Statistics

Panel B. Industry distribution in each of sample countries

		Energy	Materials	Industrials	Consumer Discretionary	Consumer Staples	Health Care	Financials	Information Technology	Telecom Services	Utilities	Industry HHI
Australia	Count	0.091	0.336	0.097	0.155	0.039	0.055	0.170	0.024	0.018	0.015	0.189
	Value	0.052	0.206	0.082	0.115	0.043	0.031	0.332	0.005	0.113	0.019	0.191
Canada	Count	0.146	0.255	0.082	0.124	0.040	0.045	0.219	0.025	0.026	0.038	0.163
	Value	0.151	0.105	0.071	0.099	0.045	0.008	0.346	0.008	0.069	0.096	0.184
France	Count	0.013	0.044	0.193	0.317	0.082	0.061	0.182	0.063	0.024	0.021	0.188
	Value	0.009	0.024	0.118	0.195	0.097	0.057	0.181	0.021	0.070	0.211	0.148
Germany	Count	0.030	0.058	0.130	0.240	0.059	0.045	0.307	0.087	0.022	0.023	0.187
	Value	0.006	0.076	0.078	0.117	0.023	0.056	0.524	0.033	0.037	0.050	0.309
Hong Kong	Count	0.029	0.077	0.130	0.358	0.075	0.034	0.204	0.041	0.036	0.015	0.204
	Value	0.051	0.043	0.097	0.210	0.053	0.013	0.321	0.030	0.140	0.043	0.186
Japan	Count	0.006	0.081	0.217	0.358	0.086	0.042	0.115	0.074	0.012	0.009	0.210
	Value	0.013	0.069	0.122	0.313	0.055	0.051	0.246	0.039	0.053	0.038	0.190
Switzerland	Count	0.006	0.049	0.165	0.189	0.073	0.093	0.327	0.045	0.010	0.043	0.190
	Value	0.002	0.042	0.078	0.059	0.122	0.260	0.386	0.009	0.022	0.020	0.244
U.K.	Count	0.047	0.064	0.184	0.305	0.046	0.048	0.205	0.054	0.020	0.028	0.184
	Value	0.019	0.096	0.082	0.150	0.108	0.083	0.255	0.012	0.074	0.120	0.142
U.S.	Count	0.064	0.064	0.125	0.154	0.040	0.130	0.189	0.187	0.024	0.023	0.138
	Value	0.079	0.047	0.106	0.121	0.103	0.122	0.164	0.174	0.047	0.038	0.120

sample countries (14,127) and the market capitalization of the U.S. ($12,701B) is almost 50% of the aggregate market capitalization of the nine developed countries ($25,368B). The cross-sectional distribution of firm size is highly right skewed in each of the nine countries. The mean of market capitalizations across individual stocks is much larger than not only the median but also the third quartile of those in every country. Also, firm size differs greatly across countries. For example, the average firm size in Switzerland ($3,817M) is about six times as large as that in Australia ($618M). Regarding the book-to-market ratio, stocks in the U.S. and the U.K. markets have relatively low book-to-market ratios of 0.68 and 0.72, respectively. In contrast, the corresponding ratios for the two Asian markets of Hong Kong and Japan are substantially higher at 1.39 and 1.25, respectively. We find that the cross-sectional distribution of book-to-market ratios is skewed to the right but not as much as that of firms' market capitalization. The mean of book-to-market ratios is between the median and the 3rd quartile of those in each country.

Panel B of Table 23 reports the industry distribution of sample firms in each of our nine sample countries. After we classify individual firms into 10 industries, determined by Global Industry Classification Standard (GICS) 10 Sector codes—energy, materials, industrials, consumer discretionary, consumer staples, health care, financials, information technology, telecommunication services, and utilities—, we compute (i) count-based industry distribution, i.e., the ratio of the number of firms in each industry to the total number of firms in that country and (ii) value-based industry distribution, i.e., the ratio of the total market value of firms in each industry to the total market value of that country. In the last column of Panel B, we report the count-based as well as value-based industry Herfindahl-Hirschman index (HHI) as a measure of industry concentration in a given country.[6]

As can be seen from Panel B of Table 23, the industry distribution of firms varies substantially from country to country. Specifically, the count-based HHI ranges from 0.138 for the U.S. to 0.210 for Japan, while the value-based HHI ranges from 0.120 for the U.S. to 0.309 for Germany. Clearly, the U.S. has the most diversified firm population across industry lines, whereas Japan and Germany have substantially more concentrated firm population. The cross-country variation is also observed in each industry. For example, the count-(value-) based share of materials is quite high for both Australia and Canada, i.e., 33.6% (20.6%) and 25.5% (10.5%), respectively, reflecting heavily resource-based nature of the two economies. No other countries have the shares of materials exceeding 10% in either count or value. In Germany, the value-based share of financials is strikingly high at 52.4%, which may be due to a small number of gigantic banks in Germany, holding both debts and equities of many German companies.[7] In Japan, consumer discretionary accounts for 35.8% (31.3%) of the

[6]The industry HHI is computed by summing over the squared count-(value-)based industry shares.

[7]As of the end of 2014, Deutsche Bank's market capitalization is 6.05% of the aggregate market capitalization of all of our sample stocks traded in Germany. It is followed by Commerzbank and KfW Bankengruppe, with the value proportions of 5.10% and 5.08%, respectively. This strong concentration of market capitalization on financial firms seems to be related to the German corporate governance system where banks play important roles as large equity holders.

total count (value) of sample firms, higher than any other industries. By comparison, consumer discretionary accounts for 12.4% (9.9%) of the total count (value) of sample firms in Canada. Due to the importance of banks in Switzerland, financials has the highest share in both count (32.7%) and value (38.6%) in the country. Perhaps reflecting the Silicon Valley effect, information technology has about the highest share in both count (18.7%) and value (17.4%) in the U.S. among all industries, which is far higher than the corresponding shares in all other countries; in Australia, for example, the count-(value-) based share of information technology is only 2.4% (0.5%). The variations in the industrial composition of national stock markets documented here suggest that firms' industry attributes may play an important role in international asset allocation strategies.

3.3 Heterogeneity in Global Integration at the Firm Level

Previous studies show that the degree of global integration differs across countries, industries, and styles (i.e., value vs. growth and large- vs. small-cap). These studies, e.g., [110], [30], [151], [16], and [29], collectively suggest that country, industry, and style may all be important dimensions affecting global integration at the firm level. In this section, we measure the degree of global integration for individual firms, by evaluating the effects of these dimensions separately and also together. We then formally test whether each of these dimensions significantly affects the degree of global integration across firms. If so, we estimate the magnitude and temporal behaviors of these effects.

3.3.1 Measuring global integration across individual firms

To measure the degree of global integration for each firm, we closely follow [151] and use the adjusted R-square from the regression of stock returns on the global factors. Specifically, for each year over our 1995–2014 sample period, we regress the weekly returns of each stock on the global factors obtained from each of the three dimensions, i.e., country, industry, and style. The adjusted R-square from the regression then measures the firm's degree of global integration. Hereafter, the adjusted R-square will be referred to as R^2 for simplicity.

To construct the global factors of the country dimension, following [151], we first estimate the weightings from the market indices of our nine sample countries during 1994 and apply the estimated weightings to the market index returns of 1995 to form the out-of-sample principal components. We then extract the first five principal components ($F^C_{j,t}$, $j = 1, \cdots, 5$) as proxies for the global factors of the country dimension in 1995, which explain at least 90% of the total volatility in the covariance matrix of the nine country market indices in 1994. We repeat this procedure each year over the whole sample period of 1995–2014 and extract the first five principal components as proxies for the global factors of the country dimension. To construct the global factors of the industry dimension, we first form the ten industry indices by value-weighting the stock returns in each industry classified by GICS. Then, similar to the procedure used in the construction of the global factors of the country dimension, we extract the first four principal components from the ten industry indices ($F^I_{j,t}$, $j = 1, \cdots, 4$) as proxies for the global factors of the industry dimension, which explain at least 90% of the total volatility in the covariance matrix of the ten industry indices in 1994. Similarly, to construct the global factors of the style dimension, we first classify all individual stocks within each of our nine sample countries into 3×3 size and book-to-market styles by independent sorting on the firm size and book-to-market ratios with the breakpoints chosen as 30%, 70% quantiles of the firm size and book-to-market ratios within each country. Then, we combine the stocks with the same style across the nine sample countries and form nine style indices by value-weighting the stock returns in each style.[8] The first two principal components ($F^S_{j,t}$, $j = 1, 2$) are then

[8]Based on the construction of the style indices, we have nine styles: small-value, small-core, small-growth, middle-value, middle-core, middle-growth, large-value, large-core, and large-growth.

extracted from the nine style indices as proxies for the global factors of the style-dimension, which explain at least 90% of the total volatility in the covariance matrix of the nine style indices in 1994.

For our main analysis of the global integration, we pool the three sets of global factors constructed separately from the country, industry, and style dimensions and use them as the global factors to estimate the R^2s for individual firms.[9,10]

To estimate the R^2s, we regress weekly stock returns on the global factors from each of the three dimensions, for each year from 1995 to 2014.

$$R_{it} = a_i^C + \sum_{j=1}^{5} b_j^C F_{jt}^C + e_{it}^C, \tag{1a}$$

$$R_{it} = a_i^I + \sum_{j=1}^{4} b_j^I F_{jt}^I + e_{it}^I, \tag{1b}$$

$$R_{it} = a_i^S + \sum_{j=1}^{2} b_j^S F_{jt}^S + e_{it}^S, \tag{1c}$$

$$R_{it} = a_i^A + \sum_{j=1}^{5} b_j^C F_{jt}^C + \sum_{j=1}^{4} b_{j+5}^I F_{jt}^I + \sum_{j=1}^{2} b_{j+9}^S F_{jt}^S + e_{it}^A, \tag{1d}$$

where R_{it} is the i-th stock return in week t; F_{jt}^C, F_{jt}^I, and F_{jt}^S are the global factors extracted from country-, industry-, and style-dimension, respectively; the superscripts "C", "I", "S", and "A" for a, b, and e indicate that the regressors are the global factors from country (C), industry (I), style (S), and all (A) of the three dimensions, respectively. Thus, the R^2s from regressions (1a) to (1d) represent the degrees of firm global integration measured from country, industry, style, and all of these three dimensions, respectively. A stock has to have at least 30 weekly returns in the sample year to enter a regression.

The cross-sectional distributions of the R^2s estimated from regressions (1a) to (1d) are summarized in Table 24. In particular, the table provides the time-series mean

[9]The results from the analysis of variance in Subsection 3.2 show that all three dimensions are indeed statistically significant in estimating firm's degree of globalization.

[10]Robustness checks for the alternative global factors are provided in Section 6.

and standard deviation of the cross-sectional average R^2s of all sample firms for each dimension, along with the minimum, 5th, 25th, 50th, 75th, and 95th percentiles, maximum, and skewness of the R^2s. Panel A of Table 24 reports the results from the entire sample period, 1995–2014, while Panels B and C of Table 24 report the results from the two equally divided sub-sample periods, 1995–2004 and 2005–2014.

Table 24: Distribution of Firm-level R2 Measured from Country, Industry, Style, and All Three Dimensions

This table summarizes the cross-sectional distribution of R^2s for country, industry, style, and all of these three dimensions. The summary statistics in the row of country, industry, style, and all of the three dimensions are computed from the cross-sectional distribution of R^2 estimated from equations (1a), (1b), (1c), and (1d), respectively. Reported numbers in Panel A are the averages over the entire sample period of 1995-2014. Corresponding numbers from the two equally divided sub-sample periods of 1995-2004 and 2005-2014 are presented in Panels B and C, respectively.

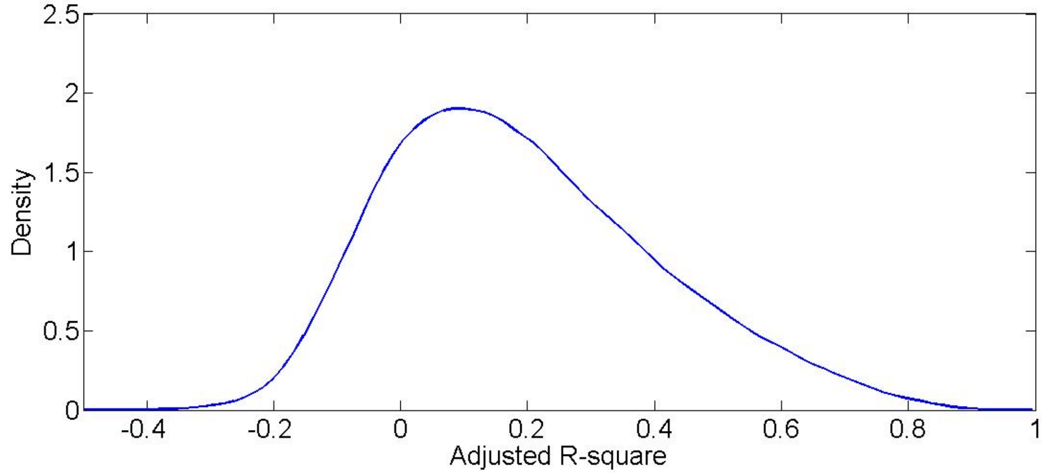
	Mean	Std	Minimum	5th percentile	25th percentile	Median	75th percentile	95th percentile	Maximum	Skewness
Panel A: 1995 to 2014										
Country	0.151	0.183	-0.196	-0.069	0.012	0.107	0.252	0.523	0.936	0.993
Industry	0.128	0.171	-0.156	-0.064	0.000	0.082	0.211	0.482	0.923	1.229
Style	0.131	0.157	-0.074	-0.037	0.008	0.085	0.211	0.453	0.903	1.259
All	0.193	0.214	-0.506	-0.111	0.033	0.166	0.331	0.590	0.939	0.496
Panel B: 1995 to 2004										
Country	0.115	0.162	-0.196	-0.075	-0.004	0.076	0.197	0.445	0.936	1.149
Industry	0.095	0.144	-0.156	-0.068	-0.011	0.058	0.163	0.392	0.874	1.305
Style	0.095	0.128	-0.074	-0.038	-0.004	0.057	0.160	0.359	0.857	1.292
All	0.157	0.196	-0.506	-0.121	0.012	0.132	0.280	0.520	0.938	0.530
Panel C: 2005 to 2014										
Country	0.186	0.196	-0.190	-0.061	0.033	0.145	0.306	0.572	0.917	0.804
Industry	0.160	0.187	-0.152	-0.059	0.015	0.112	0.261	0.543	0.923	1.042
Style	0.165	0.175	-0.074	-0.034	0.027	0.120	0.263	0.520	0.903	1.046
All	0.229	0.224	-0.480	-0.098	0.060	0.205	0.380	0.637	0.939	0.392

A few things are noteworthy from Panel A of Table 24. Most importantly, our individual sample firms exhibit a very wide range of distribution in the degree of global integration over the whole sample period of 1995-2014. Specifically, the (adjusted) R^2 estimated from all three dimensions ranges from -0.506 to 0.939, with a relatively modest median (mean) R^2 value of 0.166 (0.193), while the 5th and 95th percentiles of estimated R^2s are -0.111 and 0.590, respectively. Also, the distribution shows a skewness to the right. The wide distribution of R^2 implies that some firms are highly globally integrated but, at the same time, there are plenty of other firms with only limited exposures to the common global factors. The same stark heterogeneity in the firm-level integration is illustrated in Figure 6, which shows that individual firms are essentially distributed continuously on the integration scale. As will be shown in the following sections, the relatively 'local' stocks prove to be very useful for global diversification.

It is also noted from Panel A of Table 24 that the time-series mean of cross-sectional average R^2 (0.193) estimated from all three dimensions is substantially higher than the mean R^2 estimated from each separate dimension, i.e., country (0.151), industry (0.128), or style (0.131); the mean R^2s estimated separately from each of the three dimensions are roughly comparable to each other, although the mean R^2 from the country-dimension is somewhat higher than those from the industry or style dimensions. Similarly, the range of distribution of R^2s estimated from the all the dimensions is much greater than that estimated separately from each dimension, although each separately estimated R^2s still exhibit a strong heterogeneity, albeit attenuated, across individual firms. The R^2 distribution from all three dimensions shows a skewness that is much more modest than that from each separate dimension, making the R^2 distribution much more symmetric. Our results here again broadly suggest that all three dimensions may be important in assessing the degree of global integration even if they may not be orthogonal to each other.

It is well recognized that stock markets have become more integrated in recent decades (e.g., [15], [151], [69], and [8]). This raises an important question: Did global integration previously documented diminish or even eliminate the heterogeneity in global integration across firms? To examine this question, we compare the distributions of the degree of firm-level integration between two equally divided subsample

A. Distribution of R^2 over the whole sample period, 1995-2014



B. Distribution of R^2 over two sub-sample periods, 1995-2004 and 2005-2014

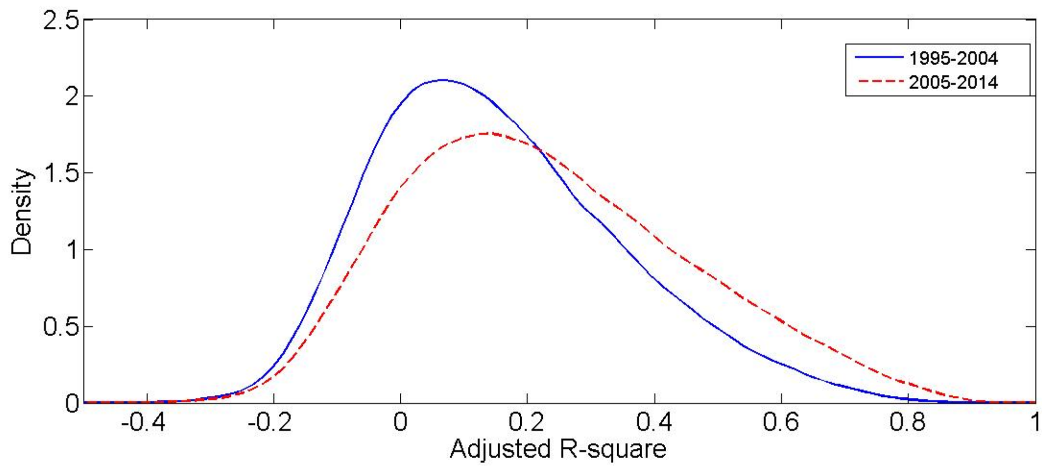


Figure 6: Distribution of the Firm-level R2

This figure plots the empirical density of R^2 measured from equation (1d) for all firms in our nine sample countries over the entire sample period of 1995-2014 (Figure 1A), and two sub-sample periods of 1995-2004 and 2005-2014 (Figure 1B). For Figure 1B, the solid line represents the distribution over the earlier sub-sample period, and the dashed line represents the distribution over the recent sub-sample period.

periods, 1995-2004 and 2005-2014. The results are provided in Panels B and C of Table 24 and also in Figure 6B. As can be seen from the panels, the mean (median) R^2 estimated from all three dimensions increased from 0.157 to 0.229 (0.132 to 0.205) over the two subsample periods, ranging from -0.506 to 0.938 in the earlier period and from -0.480 to 0.939 in the later period. Thus, both the mean and median of R^2s have increased somewhat over time, consistent with the increased integration at the firm-level, although its range remains very stable. Even in the later subsample period, the distribution of R^2 is widespread from negative to positive. Thus, there still exist plenty of individual stocks that are highly immune to the common global factors in the recent years.

To further investigate the heterogeneity in globalization at the firm-level, we generate the distribution of R^2s estimated from all three dimensions within each of our nine sample countries and summarize their distributions over the entire sample period and two sub-sample periods in Table 25. As shown in the table, firms exhibit wide ranges of R^2s over the whole sample period and two sub-sample periods in each country, pointing to the heterogeneous degrees of integration across firms within each country. For example, the R^2 ranges from -0.483 to 0.932 in Australia over the whole sample period, -0.480 to 0.915 in Germany, and -0.464 to 0.934 in the U.S. It is also noted that different countries show different distributions of globalization over time. For example, Canada, Switzerland, and the U.S. became much more integrated over time, compared to the other countries. In contrast, Hong Kong and Japan show very stable distributions of R^2s over time. Within each country, however, individual firms show stark differences in the degree of globalization. We also examine the distribution of firm-level R^2s within each industry and style and find similarly strong heterogeneity in the degree of global integration across firms within each industry and style.

Overall, the distributions of the R^2s indicate a strong heterogeneity in the degree of global integration at the firm-level. Although firms, in general, have become

Table 25: Distribution of Firm-level R2 within Each Sample Country

This table reports the summary statistics of the cross-sectional distribution of R^2 from equation (1d) averaged over the periods of 1995-2014 (Panel A), 1995-2004 (Panel B), and 2005-2014 (Panel C) for each of our nine sample countries –Australia, Canada, France, Germany, Hong Kong, Japan, Switzerland, the U.K., and the U.S. Std, Min, Max, and Skew represent standard deviation, minimum, maximum, and skewness, respectively.

				percentile						
Country	Mean	Std	Min	5th	25th	50th	75th	95th	Max	Skew
Panel A: 1995 to 2014										
Australia	0.165	0.210	-0.483	-0.138	0.012	0.139	0.295	0.558	0.932	0.529
Canada	0.242	0.232	-0.399	-0.092	0.065	0.213	0.399	0.672	0.919	0.418
France	0.173	0.215	-0.440	-0.124	0.018	0.141	0.295	0.590	0.922	0.672
Germany	0.147	0.208	-0.480	-0.144	-0.002	0.121	0.268	0.542	0.915	0.610
Hong Kong	0.154	0.206	-0.506	-0.136	0.003	0.127	0.282	0.540	0.938	0.564
Japan	0.245	0.200	-0.441	-0.065	0.098	0.232	0.383	0.595	0.885	0.216
Switzerland	0.224	0.212	-0.392	-0.091	0.071	0.207	0.356	0.621	0.883	0.382
U.K.	0.134	0.202	-0.482	-0.155	-0.009	0.111	0.251	0.516	0.939	0.603
U.S.	0.186	0.216	-0.464	-0.104	0.022	0.150	0.322	0.601	0.934	0.649
Panel B: 1995 to 2004										
Australia	0.124	0.183	-0.483	-0.147	-0.006	0.107	0.239	0.450	0.860	0.423
Canada	0.151	0.187	-0.399	-0.123	0.016	0.132	0.266	0.500	0.894	0.490
France	0.117	0.174	-0.440	-0.131	-0.008	0.100	0.219	0.439	0.892	0.643
Germany	0.118	0.179	-0.455	-0.150	-0.009	0.105	0.225	0.437	0.840	0.473
Hong Kong	0.161	0.208	-0.506	-0.141	0.011	0.139	0.286	0.545	0.938	0.531
Japan	0.247	0.202	-0.441	-0.067	0.099	0.236	0.387	0.595	0.885	0.178
Switzerland	0.175	0.192	-0.392	-0.102	0.040	0.160	0.287	0.526	0.842	0.517
U.K.	0.091	0.174	-0.482	-0.169	-0.030	0.077	0.199	0.398	0.869	0.457
U.S.	0.137	0.187	-0.464	-0.117	-0.002	0.106	0.249	0.495	0.903	0.697
Panel C: 2005 to 2014										
Australia	0.192	0.222	-0.408	-0.130	0.028	0.166	0.332	0.606	0.932	0.471
Canada	0.299	0.238	-0.396	-0.060	0.114	0.283	0.474	0.710	0.919	0.222
France	0.231	0.236	-0.400	-0.113	0.055	0.201	0.387	0.667	0.922	0.424
Germany	0.167	0.223	-0.480	-0.141	0.002	0.136	0.303	0.584	0.915	0.569
Hong Kong	0.151	0.204	-0.462	-0.135	-0.001	0.122	0.280	0.538	0.920	0.582
Japan	0.243	0.199	-0.399	-0.063	0.097	0.230	0.380	0.596	0.856	0.249
Switzerland	0.265	0.219	-0.379	-0.077	0.102	0.257	0.412	0.658	0.883	0.217
U.K.	0.176	0.217	-0.420	-0.135	0.018	0.152	0.307	0.583	0.939	0.515
U.S.	0.261	0.234	-0.414	-0.076	0.078	0.233	0.428	0.685	0.934	0.377

more globally integrated over time, there still exist a large number of firms that are minimally exposed to the common global factors. As we will discuss later in detail, stocks of these local firms would allow investors to achieve effective international diversification.

3.3.2 The effects of country, industry, and style attributes on the degree of global integration

Preceding analysis documents that firms are highly heterogenous in the degree of global integration, and country, industry, and style dimensions may be all important in determining the degree of integration. In this subsection, we formally test whether the country, industry, and style dimensions indeed significantly affect the degree of global integration at the firm level. If so, we then examine how individual country, industry, and style affect the degree of globalization.

To formally test the effect of country, industry, and style on the degree of global integration at the firm-level, we apply the analysis of variance (ANOVA) and consider the following model,

$$R^2_{it} = \alpha_t + \beta^C_{jt} + \beta^I_{kt} + \beta^S_{lt} + \epsilon_{it}, \tag{2}$$

where R^2_{it} is the degree of global integration for the i-th firm in year t estimated from equation (1d); the i-th firm belongs to the j-th country, k-th industry, and l-th style. Thus, β^C_{jt}, β^I_{kt}, and β^S_{lt} represent the effects of country j, industry k, and style l, respectively, in year t; ϵ_{it} is the firm-specific component and α_t is a common effect that all firms share.

For each year from 1995 to 2014, we estimate α, β^C, β^I, and β^S by running a cross-sectional regression of the R^2s of all sample firms on a set of country, industry, and style dummy variables,

$$R^2_i = \alpha + \sum_{j=1}^{9} \beta^C_j I^C_{ij} + \sum_{k=1}^{10} \beta^I_k I^I_{ik} + \sum_{l=1}^{9} \beta^S_l I^S_{il} + \epsilon_i, \tag{3}$$

where $I_{ij}^C = 1$ if firm i belongs to country j (zero otherwise), $I_{ik}^I = 1$ if firm i belongs to industry k (zero otherwise), and $I_{il}^S = 1$ if firm i belongs to style l (zero otherwise).

There is a perfect multicollinearity in the estimation of equation (3). ANOVA requires $\sum_{j=1}^{9} \beta_j^C = \sum_{k=1}^{10} \beta_k^I = \sum_{l=1}^{9} \beta_l^S = 0$ in the estimation and then we test the following three null hypotheses each year over our whole sample period of 1995–2014, (i) $H_0 : \beta_j^C = 0$ for all $j = 1, \cdots, 9$, (ii) $H_0 : \beta_k^I = 0$ for all $k = 1, \cdots, 10$, and (iii) $H_0 : \beta_l^S = 0$ for all $l = 1, \cdots, 9$. The test results for the hypothesis (i), (ii), and (iii) are summarized in the ANOVA column in Panels A, B, and C, respectively, in Table 26. For each hypothesis, the frequency of rejections is reported with the statistical significance at the 1%, 5% and 10% levels over the 20 years during the period of 1995-2014. As shown in Table 26, each of the hypotheses (i), (ii), and (iii) is rejected at the 1% significance level each year over the 20-year sample period, without exception, indicating that all three dimensions — country, style, and industry — have statistically significant effects on the global integration at the firm-level. This is consistent with our preceding findings and also indirectly justifies our choice of equation (1d) to measure the degree of global integration at the firm-level considering all three dimensions, rather than equations (1a)-(1c).

Now, to examine how individual country, industry, and style attributes affect the degree of firm global integration, following [96], we choose to estimate the individual country (β_j^C), industry (β_k^I), and style (β_l^S) effects on firm global integration relative to the common factor (α), which represents the proportion-weighted average degree of global integration over all sample firms.[11] In other words, the common factor α in equation (3) can be regarded as a benchmark — the "average firm" with the degree of global integration equal to α. Specifically, in the estimation of equation (3), we

[11]The proportion weights come from ω_j^C, ω_k^I, and ω_l^S in equation (4).

Table 26: The Effects of Firms' Country, Industry, and Style Attributes on the Degree of Global Integration

For each year over the entire sample period of 1995-2014, we estimate country ($\hat{\beta}_j^C$), industry ($\hat{\beta}_k^I$), and style ($\hat{\beta}_l^S$) effects on the degree of global integration at the firm-level from $R_i^2 = \alpha + \sum_{j=1}^{9} \beta_j^C I_{ij}^C + \sum_{k=1}^{10} \beta_k^I I_{ik}^I + \sum_{l=1}^{9} \beta_l^S I_{il}^S + \epsilon_i$. The ANOVA column of Panels A, B, and C reports the test results on the following three hypotheses: (i) $H_0 : \beta_j^C = 0$ for all $j = 1, \cdots, 9$, (ii) $H_0 : \beta_k^I = 0$ for all $k = 1, \cdots, 10$, and (iii) $H_0 : \beta_l^S = 0$ for all $l = 1, \cdots, 9$, respectively. We report the frequency of rejections is reported with the statistical significance at the 1%, 5% and 10% level over the 20 years during the entire sample period. Estimates and test results of the individual estimates for β_j^C for $j = 1, \cdots, 9$, β_k^I for $k = 1, \cdots, 10$, and β_l^S for $l = 1, \cdots, 9$ are summarized in the following columns. We report the averages over 1995- 2014 of the country effects (Panel A), the industry effects (Panel B), the style effects (Panel C) along with the rejection frequencies on the null of no effects at the 1%, 5%, and 10% statistical significance levels.

Panel A: Country	ANOVA	Australia	Canada	France	Germany	Hong Kong	Japan	Switzerland	U.K.	U.S.	
Mean of β_j^C		-0.040	0.021	-0.022	-0.057	-0.031	0.053	0.026	-0.060	0.008	
No. of rejections at 1%	20	15	16	14	19	19	18	6	16	18	
No. of rejections at 5%	20	17	16	15	20	19	19	7	18	18	
No. of rejections at 10%	20	18	17	15	20	19	20	8	18	18	
Panel B: Industry	ANOVA	Energy	Materials	Industrials	Consumer Discretionary	Consumer Staples	Health Care	Financials	Information Technology	Telecom Services	Utilities
Mean of β_k^I		0.051	0.023	0.005	-0.013	-0.048	-0.040	0.012	0.019	-0.003	-0.014
No. of rejections at 1%	20	16	13	12	14	20	17	13	13	9	10
No. of rejections at 5%	20	20	16	12	16	20	17	15	14	13	11
No. of rejections at 10%	20	20	18	14	16	20	17	15	15	15	14
Panel C: Style	ANOVA	Small Growth	Small Core	Small Value	Mid Growth	Mid Core	Mid Value	Large Growth	Large Core	Large Value	
Mean of β_l^S		-0.107	-0.102	-0.111	-0.035	-0.017	-0.019	0.101	0.123	0.116	
No. of rejections at 1%	20	20	20	20	18	15	14	20	20	20	
No. of rejections at 5%	20	20	20	20	19	15	16	20	20	20	
No. of rejections at 10%	20	20	20	20	19	16	17	20	20	20	

first set $\beta_9^C = 0$, $\beta_{10}^I = 0$, and $\beta_9^S = 0$ and then we impose the following restriction:

$$\sum_{j=1}^{9} \omega_j^C \beta_j^C = 0, \ \sum_{k=1}^{10} \omega_k^I \beta_k^I = 0, \ \sum_{l=1}^{9} \omega_l^S \beta_l^S = 0, \tag{4}$$

where ω_j^C, ω_k^I, and ω_l^S are the proportions of firms in country j, in industry k, and in style l among all sample firms in terms of the number of firms.[12]

The time-series means of the country effects $\hat{\beta}_j^C$, $j = 1, \cdots, 9$, the industry effects $\hat{\beta}_k^I$, $k = 1, \cdots, 10$, and the style effects $\hat{\beta}_l^S$, $l = 1, \cdots, 9$ over the whole sample period of 1995–2014 are provided in Table 26, along with the rejection frequencies of the null of no effects at the 1%, 5%, and 10% levels of significance.

As shown in Table 26, country, industry, and style attributes exert very different effects on the degree of global integration at the firm-level. In particular, for the country attribute, firms from Canada, Japan, Switzerland, and the U.S., on average, tend to be more integrated than the average firm (with the degree of integration given by $\hat{\alpha}$) by 0.021, 0.053, 0.026, and 0.008, respectively, while firms from Australia, France, Germany, Hong Kong, and the U.K. are less integrated than the average firm by 0.040, 0.022, 0.057, 0.031, and 0.060, respectively. For the industry attribute, firms in the consumer discretionary, consumer staples, health care, telecom services, and utilities are, on average, less integrated than the average firm by 0.013, 0.048, 0.040, 0.003, and 0.014, respectively. These results are largely as expected since the above industries are generally considered less or non-tradable industries. In contrast, firms in the energy, materials, industrials, financials, and information technology are more integrated than the average firm by 0.051, 0.023, 0.005, 0.012, and 0.019, respectively. For the style dimension, small-growth, small-core, and small-value firms are, on average, less integrated than the average firm by 0.107, 0.102, and 0.111, respectively. Also, mid-growth, mid-core, and mid-value firms are less integrated than the average firm by 0.035, 0.017, and 0.019, respectively, which are somewhat

[12] The estimation results do not change qualitatively when we change the restriction of (4) to $\sum_{j=1}^{9} \beta_j^C = \sum_{k=1}^{10} \beta_k^I = \sum_{l=1}^{9} \beta_l^S = 0$.

weaker than small firms. In contrast to small- and middle-size firms, large-growth, large-core, and large-value firms are more integrated than the average firm by 0.101, 0.123, and 0.116, respectively. Remarkably, the coefficients for small as well as large size firms are all significant at the 1% level each year over the entire sample period, without exception. These results are consistent with the findings of previous literature that large firms tend to be more integrated globally, as these firms have high liquidity, low information asymmetry, few barriers in trading, and good governance (e.g., [110] and [29]).

In order to examine the time trends in the country, industry, and style effects on the degree of firm global integration, following [155], we compute the mean absolute deviations (MAD) of the three dimensions: Country MAD as $\sum_{j=1}^{9} \omega_j^C |\hat{\beta}_j^C|$, industry MAD as $\sum_{k=1}^{10} \omega_k^I |\hat{\beta}_k^I|$, and style MAD as $\sum_{l=1}^{9} \omega_l^S |\hat{\beta}_l^S|$. The time-series of country, industry, and style MADs over our whole sample period, 1995-2014, are plotted in Figure 7. As shown in the figure, the style dimension has, on average, the largest effect on the degree of global integration followed by the country dimension and the industry dimension. The country and style MADs have larger volatility than the industry MAD.

To further investigate the time trends in the country, industry, and style effects on the degree of firm global integration, we examine the time-trend for each individual country, industry, and style attribute. As shown in the table, different countries, industries, and styles show different time trends in their effects on the degree of global integration at the firm-level. For example, the effect of the U.S. on the firm global integration is negative, relative to the average firm, during the earlier years, but became positive from 2007, probably reflecting the sub-prime mortgage crisis and the Great Recession. Information technology shows positive effects during the earlier years, but became negative during the recent years, implying that firms in information technology did not become more integrated over time. Small (large)-growth, -core,

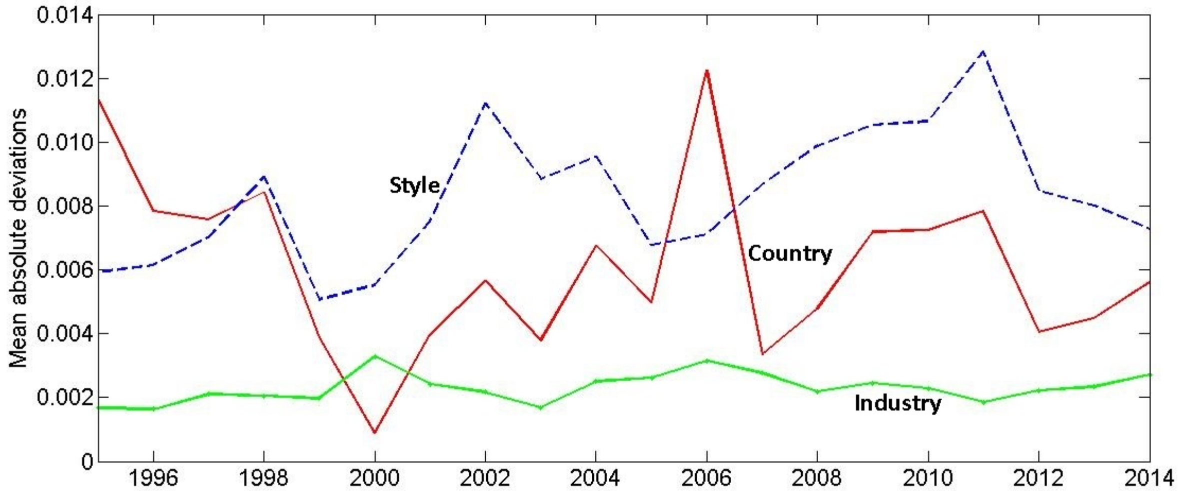


Figure 7: The Aggregate Effects of Country, Industry, and Style Attributes on the Firm-level R2

This figure plots the time-series of country, industry, and style mean absolute deviations (MAD) over our entire sample period of 1995-2014. First, we estimate country ($\hat{\beta}_j^C$), industry ($\hat{\beta}_k^I$), and style ($\hat{\beta}_l^S$) effects on the degree of global integration across firms in each year using $R_i^2 = \alpha + \sum_{j=1}^{9} \beta_j^C I_{ij}^C + \sum_{k=1}^{10} \beta_k^I I_{ik}^I + \sum_{l=1}^{9} \beta_l^S I_{il}^S + \epsilon_i$. Then, we compute the MAD of the three dimensions: country MAD as $\sum_{j=1}^{9} \omega_j^C |\hat{\beta}_j^C|$, industry MAD as $\sum_{k=1}^{10} \omega_k^I |\hat{\beta}_k^I|$, and style MAD as $\sum_{l=1}^{9} \omega_l^S |\hat{\beta}_l^S|$, where ω_j^C is the proportion of firms in country j among all firms in our nine sample countries in terms of market capitalization, ω_k^I is the proportion of firms in industry k, and ω_l^S is the proportion of firms in style l.

and -value styles show negative (positive) effects on the global integration among firms for each of the 20 years over our whole sample period, thus exhibiting very consistent effects of style attribute on the degree of global integration at the firm-level.

Overall, all three dimensions of firm attributes, i.e., country, industry, and style, are statistically significant in explaining the degree of firm global integration. The style dimension has the largest aggregate effect on the degree of global integration at the firm-level, while the industry dimension has the smallest aggregate effect. Meanwhile, individual country, industry, and style attributes have different, time-varying effects on the firm-level global integration in terms of the magnitude and direction (i.e., positive or negative) of the effect.

3.4 Portfolio Risk Diversification with Local Stocks

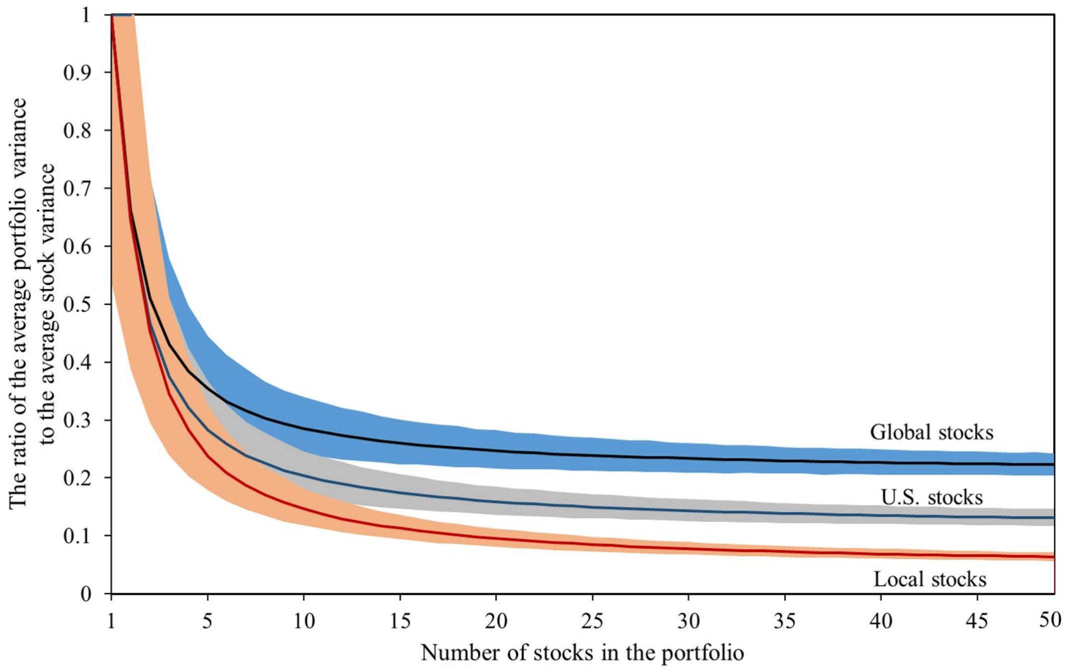
Having documented a strong heterogeneity in the degree of global integration at the firm level, we now turn to some of the practical implications of this heterogeneity for international portfolio investment. In particular, we estimate the potential gains in terms of risk reduction from international diversification with "local stocks" whose returns are least driven by common global factors. Based on the wide distribution of R^2 at the firm level, shown in the previous section, we conjecture that if investors systematically identify local stocks and form portfolios with these stocks, they are most likely to benefit significantly in terms of extra risk reduction beyond the conventional diversification gains with purely domestic stocks. To test this conjecture, we compare the effectiveness of portfolio diversification with three distinct groups of individual stocks, i.e., global, local, and U.S. stocks.

Specifically, we use the simulation method employed by [161]. As described in Section 3, we first regress weekly stock returns on the global factors and estimate R^2 of each individual stock at the end of each year over our sample period 1995-2014. Then, we define global (local) stocks as those belonging to the top (bottom) decile sorted on R^2 among our international sample stocks. Following [161], we then randomly choose a varying number of stocks (ranging from 1 to 50) with replacement, from each of the three separate groups of stocks, to form equal-weighted portfolios and compute the variances of weekly portfolio returns.[13] By repeating the simulation procedure 5,000 times, we obtain so many realizations of the variance for each portfolio consisting of a certain number of stocks.

Figure 8A plots the ratio of the average of portfolio variances to the average of individual stock variances as a function of the number of stocks in a given portfolio for each of the three stock groups: global (top 10% in R^2), local (bottom 10% in R^2),

[13]Since stocks in the top (global) or bottom (local) decile change each year, we resample stocks in each year, generating the portfolio returns over the 20-year sample period from 1995 to 2014.

A. Effectiveness of portfolio risk diversification with global, local, and U.S. stocks



B. The time-series of systematic portfolio variances for global, local, and U.S. stocks

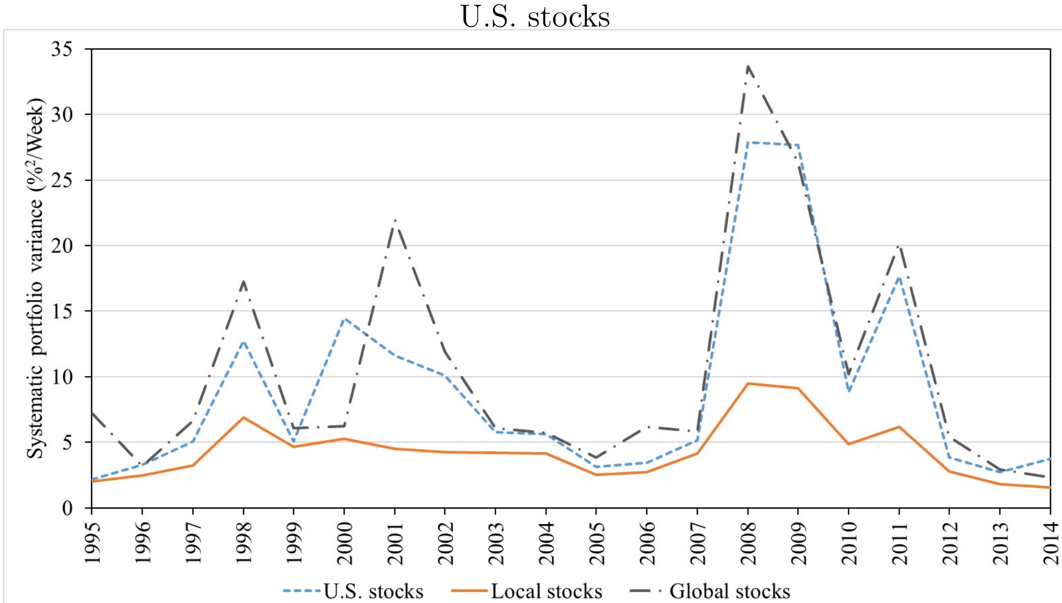


Figure 8: Portfolio Risk Diversification with Local Stocks

C. Systematic portfolio variance and the diversification gains

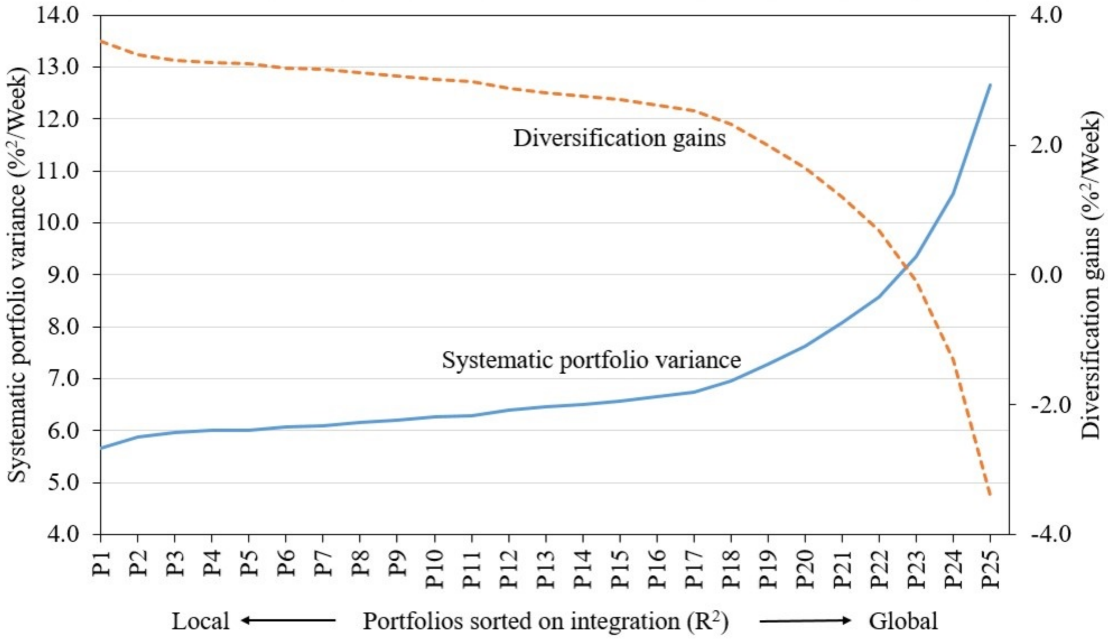


Figure 8: (Cont.) Portfolio Risk Diversification with Local Stocks

This figure shows the effectiveness of portfolio variance reduction using local stocks in comparison with using either global stocks or U.S. stocks. Figure 8A plots the ratio of the average of portfolio variances to the average of individual stock variance as a function of the number of stocks in a given portfolio for each of the three stock groups: global (top 10% in R^2), local (bottom 10% in R^2), and U.S. domestic stocks. The three solid lines represent the average of the ratios across 5,000 simulations and the color-shaded areas represent the associated 95% confidence intervals. R^2 of each individual stock is measured by regressing weekly stock returns on global factors at the end of each year over our whole sample period of 1995-2014. Following [161], we then randomly choose a varying number of stocks (ranging from 1 to 50) with replacement, from each of the three separate groups of stocks, to form equal-weighted portfolios and compute the variances of weekly portfolio returns. Figure 8B illustrates how the systematic portfolio variance (N=50) — the variance limit in Figure 8A — has been evolved over time for each of the three groups of stocks. Finally, Figure 8C plots (i) the systematic portfolio variance (solid line) computed from fully diversified portfolios (N=50) and (ii) the gains from international diversification (dashed line) over P1 through P25, where the gains from international diversification is measured by the systematic portfolio variance from U.S. stocks (9.266%^{2}/week) minus the systematic portfolio variance from each of the 25 portfolios sorted on R^2. P1 (P25) comprises the most local (global) stocks, representing the bottom (top) 4% of our sample international stocks sorted on R^2.

and U.S. stocks. The figure clearly shows that local stocks are much more effective in reducing the portfolio risk than global stocks. In fact, the average variance of fully diversified portfolios (N=50) comprising local stocks is only about 6.3% of the average variance of individual stocks, whereas the ratio goes up to 22.3% when we use global stocks.[14] With U.S. stocks, the ratio is 13.1%, falling in between the two ratios.

The first key message from Figure 8A is that U.S. investors may not necessarily benefit from international diversification *per se*. In fact, domestic diversification with U.S. stocks is much more effective in reducing the portfolio risk than international diversification with global stocks. This is likely due to the fact that some of U.S. stocks are not much affected by global factors, i.e., local, while global stocks are significantly driven by the common global factors. The second important message is that U.S. investors may continue to benefit significantly from 'selective' international diversification with local stocks that are minimally affected by the global factors. Furthermore, it is noted that the 95% confidence intervals for the systematic risks for the three "fully diversified" portfolios do not overlap each other. This implies that the gains from international diversification with local stocks, relative to U.S. domestic diversification, can be reliably achieved by simply holding a sufficiently large number of local stocks. This additional advantage of diversification with local stocks is likely due to the fact that, by construction, local stock returns are mostly driven by idiosyncratic risks. As a result, the correlations among these stocks will tend to be reliably low, keeping the systematic portfolio risk low and stable.[15] Figure

[14] Figure 8A indicates that for each stock group, the portfolio variance converges to the systematic (i.e., undiversifiable) portfolio variance level when the portfolio contains about 40 individual stocks. Thus, a portfolio can be considered fully diversified if it contains 40 or more stocks. To be conservative, however, we compute the systematic portfolio variance at N=50 in the ensuing analysis.

[15] The average pairwise correlation of weekly individual stock returns within the global (top 10% in R^2) and local (bottom 10% in R^2) portfolios are 0.280 and 0.063, respectively, during our sample period of 1995-2014.

8A indeed shows that the confidence interval for the systematic risk of the local stock portfolio is very tight.

Next, we examine the time-series pattern in the systematic variance of portfolios ($N = 50$) consisting of global, local, and U.S. stocks. At the end of each year, we form decile portfolios based on individual stock R^2s eatimated in that year, and randomly pick 50 stocks from U.S. stocks, global stocks (top 10% in R^2), and local stocks (bottom 10% in R^2) and calculate equal-weighted portfolio returns using selected stock returns in the next year. We repeat this process 5,000 times. Figure 8B illustrates how the systematic portfolio variance has evolved over time for each of the three types of stocks. The figure reveals a consistent pattern that the systematic portfolio variance is always highest for global stocks and lowest for local stocks, with the systematic variance for U.S. stocks falling in between. Remarkably, the systematic portfolio variance of local stocks did not increase noticeably even during the crisis years, such as 1998 (the aftermath of Asian/Russian financial crises), 2000-2001 (the dotcom bubble burst and the 9/11 incident), and 2008-2011 (the U.S. subprime mortgage crisis and the European sovereign debt crisis). It is noteworthy that the systematic portfolio variance of local stocks rose only modestly during 1998 and 2000, and also during 2008-2009. In a sharp contrast, the systematic portfolio variances of both global and U.S. stocks rose dramatically in each of those years, instigating negative comments from investors like, "Where are the diversification benefits when we need it most?" However, as shown in Figure 8B, local stocks can serve as an effective safe-haven (if not completely calm) from the extreme volatilities observed during those global financial crises. At the height of sub-prime mortgage crisis in 2008, for instance, the variance of the local stock portfolio returns (computed from weekly returns in dollar terms) was $9.51\%^2$, strikingly lower than 27.85 $(33.67)\%^2$ for the U.S. (global) stock portfolio. In other words, the gains from international risk reduction with local stocks, relative to domestic diversification with U.S. stocks, remain robust during the crisis periods, a valuable trait for local stocks.

Incidentally, the results in Figures 8A-8B suggest that there can be a systematic relation between stock market integration and the magnitude of systematic portfolio variance (and thus the gains from international diversification). To pursue this point further, we construct 25 portfolios (P1 through P 25) more finely sorted on R^2 and investigate how the systematic portfolio risk may be related to the degree of global integration of stocks. These portfolios are constructed essentially in the same way as the decile portfolios used in the above analysis except we use 25 portfolios. P1 (P25) comprises the most local (global) stocks, representing the bottom (top) 4% of our sample international stocks sorted on R^2. Figure 8C plots the systematic portfolio variance computed from fully diversified portfolios (N=50) over the entire spectrum of integration, P1 through P25. Along with the systematic portfolio variance, we overlay the gains from international diversification where the gains are measured by the systematic portfolio variance from U.S. stocks (13.1%^{2}/week) minus the systematic portfolio variance from each of the 25 portfolios sorted on R^2.[16] Figure 8C indicates that as the degree of global integration increases, the systematic portfolio variance (solid line) rises at a slow pace until about P17, but afterwards increases at a much faster rate, probably reflecting the right skewness of the firm-level R^2 distribution documented in the previous section (see Figure 6). On the other hand, the gains from international diversification (dotted line) behave as a mirror image of the systematic portfolio risk over P1 through P25, initially declining slowly but then at a faster rate later. It is noteworthy, however, that the diversification gains remain positive untill P22 and turn negative only for the most integrated portfolios, P23-P25.

Table 27 provides detailed numerical information pertaining to the relation illustrated in Figure 8C, including (i) the systematic portfolio variance, estimated at

[16] [46] propose a similar method in measuring the gains from housing portfolio diversification.

Table 27: Characteristics of 25 Portfolios Sorted on the Firm-level R2

This table provides detailed numerical information pertaining to the relation illustrated in Figure 8C, including (i) the systematic portfolio variance, estimated at N=50, along with the associated 95% confidence interval, and the magnitude of diversification gains for each portfolio relative to the well-diversified U.S. portfolio and (ii) the averages of R^2, pairwise correlation, and the variance of (weekly) returns for individual stocks comprising each portfolio. R^2 of each individual stock is measured by regressing weekly stock returns on global factors at the end of each year over our sample period 1995-2014. P1 (P25) comprises the most local (global) stocks, representing the bottom (top) 4% of our sample international stocks sorted on R^2. We then randomly choose 50 stocks with replacement, from each of 25 portfolios to form equal-weighted returns and compute the variances of weekly portfolio returns. The systematic portfolio variance is the average, across 5,000 simulations, of the variances of weekly portfolio returns comprising the 50 selected stocks in each simulation. We also obtain the 95% confidence interval from the same simulation exercise.

	Systematic	95% Confidence Interval		Diversification	Averages over Individual Stocks		
	Portfolio Variance ($\%^2$/week)	Lower Limit	Upper Limit	Gains ($\%^2$/week)	Degree of Integration (R^2)	Pairwise Correlation	Variance ($\%^2$/week)
P1	5.665	5.086	6.350	3.601	0.123	0.058	91.740
P2	5.874	5.304	6.710	3.393	0.171	0.066	92.736
P3	5.957	5.347	6.639	3.309	0.199	0.073	90.450
P4	6.004	5.410	6.733	3.263	0.221	0.076	88.699
P5	6.013	5.392	6.711	3.254	0.241	0.079	86.234
P6	6.083	5.462	6.765	3.184	0.258	0.085	85.331
P7	6.103	5.374	6.716	3.163	0.275	0.090	83.821
P8	6.157	5.643	6.990	3.109	0.291	0.095	81.553
P9	6.204	5.475	6.833	3.063	0.307	0.099	77.135
P10	6.258	5.592	6.990	3.009	0.322	0.105	79.766
P11	6.291	5.622	6.934	2.976	0.337	0.109	76.027
P12	6.395	5.816	7.233	2.871	0.353	0.119	75.849
P13	6.455	5.863	7.265	2.812	0.369	0.122	73.784
P14	6.508	5.701	6.996	2.758	0.385	0.131	71.220
P15	6.569	5.814	7.118	2.698	0.402	0.137	67.974
P16	6.661	6.012	7.360	2.606	0.420	0.144	69.008
P17	6.747	6.090	7.474	2.519	0.438	0.149	67.522
P18	6.950	6.239	7.638	2.317	0.457	0.159	63.278
P19	7.271	6.575	8.019	1.996	0.479	0.174	61.493
P20	7.617	6.890	8.382	1.650	0.502	0.182	60.501
P21	8.077	7.185	8.742	1.190	0.528	0.193	58.119
P22	8.578	7.801	9.407	0.688	0.558	0.211	55.996
P23	9.357	8.660	9.929	-0.090	0.594	0.222	52.866
P24	10.569	9.524	11.367	-1.302	0.642	0.260	49.483
P25	12.657	11.656	13.734	-3.391	0.730	0.329	46.074

N=50, along with the associated 95% confidence interval, and the magnitude of diversification gains for each portfolio relative to the well-diversified U.S. portfolio and (ii) the averages of R^2, pairwise correlation, and the variance of (weekly) returns for individual stocks comprising each portfolio. While much of the information provided in Table 5 is largely self-explanatory, it is noteworthy that the average pairwise correlation among individual stock returns is only 0.058 for P1 but much higher at 0.329 for P25. Thus, although the individual stock volatility is obviously much higher, on average, for P1 (91.740$\%^2$/week) than for P25 (46.074$\%^2$/week), the systematic portfolio variance is much higher for P 25 (12.655$\%^2$/week) than for P1 (5.672$\%^2$/week).[17]

3.5 Mean-variance Optimization with Local Stocks

In the previous sections, we document a strong heterogeneity in the degree of global integration at the firm-level (Section 3) and the gains in terms of extra portfolio risk diversification from using local stocks (Section 4). Our goal in this section is to show how investors can effectively exploit the heterogeneity in global integration across individual firms and enhance the mean-variance efficiency of their portfolios by holding "local portfolios" optimally in conjunction with country market indices.

3.5.1 Construction of local portfolios

In this subsection, we describe how to construct the local portfolios that will be used in our mean-variance analysis and discuss the distributional properties of the local portfolio returns.

Based on our earlier finding that each of the three dimensions of firm attributes, i.e, country, industry, and style, matters in determining the degree of global integration

[17]The relation depicted in Figure 8C as well as the information provided in Table 27 strongly points to an intriguing possibility: Global financial integration may be self-defeating in the long run, in a way, as greater integration may eventually lead to higher correlations among stocks, thereby diminishing the diversification benefits. It is, however, beyond the scope of the current paper to formally investigate this possibility.

at the firm-level, we estimate the R^2s based on equation (1d) that uses as the global factors the three separate sets of principal components representing each of the three dimensions of firm attributes. We then form the (value-weighted) local portfolio for each country, industry, and style group using the bottom decile of firms sorted on the R^2s of individual sample firms classified into the group. Altogether, we form 28 local portfolios, comprising nine country, ten industry, and nine style local portfolios.

Table 28: Summary Statistics of Country Market Indices and Country-local, Industry-local, and Style-local Portfolios

This table summarizes the properties of the monthly returns of the nine country market indices and 28 (= 9 country + 10 industry + 9 style) local portfolios. Panel A reports the mean, the standard deviation (Std), and the Sharpe ratio of the monthly returns of the nine country market indices. Panels B, C, and D present those statistics of value-weighted monthly returns of local portfolios from country, industry, and style dimensions, respectively. Panel E reports the correlation matrix of the nine country market indices and the 28 local portfolios. Mean and Std are reported in percentage per month. Sharpe ratios are expressed in a monthly unit. The average monthly risk-free rate in our sample period is 0.23%.

Panel A. Country market indices

	Australia	Canada	France	Germany	Hong Kong	Japan	Switzerland	U.K.	U.S.	Average
Mean	1.035	1.110	0.930	0.907	0.945	0.170	0.978	0.780	0.941	0.866
Std	6.334	5.991	6.205	6.937	7.129	5.668	5.106	5.054	4.783	5.912
Sharpe ratio	0.130	0.150	0.115	0.100	0.103	-0.008	0.150	0.112	0.152	0.111

Panel B. Country local portfolios

	Australia	Canada	France	Germany	Hong Kong	Japan	Switzerland	U.K.	U.S.	Average
Mean	1.173	1.798	1.020	0.325	0.804	0.529	1.245	0.927	1.276	1.011
Std	9.006	6.902	5.264	5.637	7.857	5.512	5.244	5.824	5.043	6.255
Sharpe ratio	0.107	0.229	0.153	0.020	0.075	0.057	0.196	0.122	0.211	0.130

Panel C. Industry local portfolios

	Energy	Materials	Industrials	Consumer Discr.	Consumer Staples	Health Care	Financials	Information Technology	Telecom Services	Utilities	Average
Mean	0.798	0.598	0.754	0.982	0.967	1.567	1.047	1.897	1.133	1.308	1.105
Std	8.235	7.204	4.548	4.934	4.435	6.020	4.096	8.412	8.102	5.217	6.120
Sharpe ratio	0.071	0.053	0.119	0.156	0.170	0.225	0.203	0.200	0.113	0.210	0.152

Panel D. Style local portfolios

	Small Growth	Small Core	Small Value	Middle Growth	Middle Core	Middle Value	Large Growth	Large Core	Large Value	Average
Mean	0.173	0.551	1.022	0.701	0.967	1.331	0.925	1.132	1.233	0.893
Std	6.888	5.737	4.951	5.613	4.826	4.432	3.760	3.606	4.673	4.943
Sharpe ratio	-0.006	0.059	0.163	0.087	0.156	0.252	0.189	0.255	0.218	0.153

Table 28 provides summary statistics of the monthly returns of the nine country market indices and the 28 sample local portfolios. In particular, Panel A reports the mean, the standard deviation, and the Sharpe ratio of the monthly returns of each of the country market indices. Panels B, C, and D present the same statistics

Table 28: (Cont.) Summary Statistics of Country Market Indices and Country-local, Industry-local, and Style-local Portfolios

Panel E. Correlation matrix

	Country Indices									Country Locals									Industry Locals										Style Locals								
	AU	CA	FR	GE	HK	JP	SW	UK	US	AU	CA	FR	GE	HK	JP	SW	UK	US	EN	MT	ID	CD	CS	HC	FN	IT	TS	UT	SG	SC	SV	MG	MC	MV	LG	LC	LV
Country Indices																																					
Austrailia	1.00																																				
Canada	0.80	1.00																																			
France	0.74	0.76	1.00																																		
Germany	0.71	0.77	0.91	1.00																																	
Hong Kong	0.71	0.71	0.59	0.62	1.00																																
Japan	0.54	0.51	0.50	0.46	0.47	1.00																															
Switzerland	0.68	0.68	0.82	0.79	0.55	0.51	1.00																														
U.K.	0.83	0.82	0.89	0.85	0.68	0.52	0.80	1.00																													
U.S.	0.75	0.82	0.80	0.82	0.65	0.51	0.74	0.84	1.00																												
Country Locals																																					
Austrailia	0.81	0.72	0.57	0.55	0.64	0.44	0.53	0.69	0.58	1.00																											
Canada	0.62	0.75	0.60	0.58	0.51	0.33	0.56	0.66	0.59	0.60	1.00																										
France	0.49	0.54	0.64	0.60	0.35	0.33	0.54	0.58	0.44	0.50	0.50	1.00																									
Germany	0.43	0.39	0.50	0.46	0.26	0.28	0.48	0.46	0.28	0.42	0.42	0.55	1.00																								
Hong Kong	0.54	0.57	0.41	0.45	0.64	0.38	0.37	0.51	0.46	0.57	0.41	0.38	0.32	1.00																							
Japan	0.38	0.28	0.33	0.25	0.32	0.82	0.39	0.32	0.27	0.35	0.23	0.28	0.26	0.26	1.00																						
Switzerland	0.57	0.61	0.67	0.63	0.43	0.38	0.72	0.65	0.54	0.52	0.56	0.55	0.54	0.39	0.28	1.00																					
U.K.	0.58	0.61	0.60	0.55	0.49	0.35	0.49	0.69	0.48	0.59	0.56	0.56	0.38	0.45	0.23	0.60	1.00																				
U.S.	0.65	0.73	0.65	0.68	0.54	0.43	0.60	0.70	0.78	0.56	0.59	0.47	0.27	0.49	0.23	0.54	0.56	1.00																			
Industry Locals																																					
Energy	0.59	0.65	0.51	0.49	0.44	0.38	0.48	0.60	0.46	0.63	0.59	0.49	0.41	0.53	0.28	0.53	0.56	0.51	1.00																		
Materials	0.62	0.68	0.53	0.52	0.47	0.45	0.54	0.59	0.50	0.64	0.64	0.50	0.44	0.50	0.31	0.61	0.57	0.59	0.62	1.00																	
Industrials	0.65	0.70	0.68	0.65	0.55	0.57	0.64	0.72	0.64	0.63	0.61	0.63	0.46	0.55	0.46	0.57	0.63	0.70	0.63	0.65	1.00																
Cons. Disc.	0.60	0.64	0.65	0.60	0.54	0.57	0.56	0.66	0.62	0.60	0.53	0.54	0.39	0.55	0.52	0.52	0.60	0.68	0.51	0.51	0.70	1.00															
Cons. Stpl.	0.48	0.43	0.50	0.45	0.37	0.39	0.54	0.53	0.42	0.44	0.43	0.42	0.38	0.31	0.41	0.52	0.41	0.44	0.39	0.40	0.50	0.44	1.00														
Health Care	0.41	0.49	0.48	0.50	0.37	0.30	0.46	0.49	0.49	0.35	0.44	0.34	0.20	0.33	0.17	0.46	0.54	0.62	0.34	0.35	0.55	0.44	0.24	1.00													
Financials	0.64	0.59	0.59	0.55	0.54	0.47	0.58	0.67	0.55	0.63	0.55	0.58	0.50	0.49	0.40	0.56	0.61	0.56	0.54	0.60	0.68	0.61	0.48	0.35	1.00												
Info. Tech.	0.46	0.60	0.51	0.54	0.47	0.45	0.39	0.53	0.58	0.46	0.42	0.38	0.20	0.43	0.33	0.41	0.51	0.65	0.37	0.43	0.57	0.60	0.23	0.50	0.39	1.00											
Tele. Serv.	0.53	0.53	0.48	0.49	0.51	0.39	0.46	0.55	0.53	0.50	0.44	0.36	0.29	0.44	0.31	0.39	0.40	0.52	0.41	0.37	0.49	0.52	0.31	0.36	0.44	0.48	1.00										
Utilities	0.34	0.37	0.31	0.33	0.27	0.22	0.32	0.36	0.26	0.31	0.29	0.29	0.28	0.37	0.20	0.34	0.32	0.30	0.37	0.35	0.42	0.33	0.30	0.20	0.37	0.20	0.23	1.00									
Style Locals																																					
Small Growth	0.60	0.62	0.55	0.52	0.55	0.49	0.45	0.59	0.52	0.64	0.54	0.54	0.36	0.63	0.39	0.53	0.56	0.56	0.50	0.55	0.64	0.63	0.39	0.45	0.61	0.56	0.48	0.31	1.00								
Small Core	0.54	0.62	0.54	0.52	0.46	0.42	0.46	0.57	0.50	0.58	0.50	0.54	0.41	0.56	0.29	0.55	0.66	0.58	0.49	0.56	0.65	0.61	0.36	0.52	0.56	0.58	0.43	0.25	0.65	1.00							
Small Value	0.55	0.66	0.54	0.53	0.49	0.44	0.46	0.60	0.55	0.61	0.53	0.54	0.40	0.53	0.28	0.55	0.69	0.63	0.58	0.59	0.71	0.66	0.36	0.52	0.60	0.59	0.44	0.34	0.61	0.71	1.00						
Mid Growth	0.65	0.73	0.65	0.66	0.59	0.54	0.54	0.67	0.67	0.62	0.56	0.57	0.35	0.59	0.39	0.57	0.68	0.72	0.54	0.59	0.75	0.71	0.39	0.62	0.57	0.73	0.52	0.33	0.70	0.71	0.74	1.00					
Mid Core	0.67	0.73	0.63	0.64	0.55	0.49	0.57	0.69	0.60	0.67	0.63	0.60	0.45	0.60	0.36	0.64	0.71	0.67	0.67	0.74	0.78	0.67	0.45	0.53	0.67	0.58	0.49	0.37	0.69	0.77	0.75	0.80	1.00				
Mid Value	0.68	0.72	0.69	0.66	0.54	0.48	0.63	0.74	0.64	0.64	0.65	0.62	0.46	0.59	0.37	0.62	0.70	0.73	0.70	0.67	0.87	0.72	0.51	0.58	0.72	0.56	0.49	0.47	0.67	0.69	0.76	0.76	0.81	1.00			
Large Growth	0.57	0.61	0.68	0.64	0.48	0.51	0.69	0.70	0.69	0.48	0.59	0.47	0.35	0.41	0.43	0.56	0.51	0.67	0.41	0.50	0.69	0.69	0.62	0.51	0.60	0.47	0.47	0.39	0.52	0.50	0.50	0.58	0.58	0.69	1.00		
Large Core	0.70	0.74	0.77	0.74	0.60	0.61	0.77	0.80	0.75	0.60	0.66	0.56	0.47	0.49	0.48	0.62	0.58	0.71	0.60	0.64	0.78	0.69	0.62	0.49	0.71	0.50	0.51	0.42	0.59	0.53	0.58	0.66	0.70	0.78	0.78	1.00	
Large Value	0.64	0.70	0.70	0.68	0.50	0.46	0.66	0.74	0.70	0.55	0.54	0.55	0.39	0.41	0.30	0.54	0.58	0.70	0.54	0.58	0.69	0.61	0.40	0.48	0.60	0.47	0.37	0.42	0.52	0.52	0.64	0.63	0.65	0.74	0.59	0.73	1.00

for the local portfolios from country, industry, and style dimensions, respectively. Panel E reports the correlation matrix among all our sample market indices and local portfolios.

Panel A shows that measured by the Sharpe ratio, the U.S. market index (0.152) performed the best, followed by Canada (0.150), Switzerland (0.150), Australia (0.130), France (0.115), the U.K. (0.112), Hong Kong (0.103), Germany (0.100), and Japan (-0.008) during our sample period 1995-2014. Japan is the only country with a negative Sharpe ratio, which is due to its exceptionally low mean return, 0.170%, which is compared with the sample cross-country average mean return of 0.866%. This low mean return of the Japanese market index is probably reflective of the so-called lost decades of the country. With its relatively modest mean return, the strong performance of the U.S. market is attributable to its low risk; the standard deviation of returns of the U.S. market index (4.783%) is the lowest among all our sample market indices.

Panels B, C, and D indicate that each of the three types of local portfolios, on average, has a substantially higher Sharpe ratio than the country market indices — in particular, the average Sharpe ratio is 0.111 for the country market indices, which is compared with 0.130 for the country local portfolios, 0.152 for the industry local portfolios, and 0.153 for the style local portfolios. It is noteworthy from the panels that quite a few individual local portfolios registered very strong performances — in particular, the large-core local portfolio has the highest Sharpe ratio (0.255) among all the local portfolios, followed by the middle-value local (0.252), Canada local (0.229), health care local (0.225), large-value local (0.218), U.S. local (0.211), utilities local (0.210), financials local (0.203), and information technology local (0.200). It is also interesting to note that value-oriented local portfolios and also local portfolios from less- or non-traded industries, such as health care and utilities, are well represented among the top performing local portfolios. During our sample period, the above local portfolios substantially outperformed the best performing country market index, i.e., the U.S. index with a Sharpe ratio of 0.152.

Panel E presents the correlation matrix for the nine country market indices, nine country local portfolios, ten industry local portfolios, and nine style local portfolios. The correlation matrix indicates that the average correlation is 0.44 among country local portfolios and also among industry local portfolios, which is substantially lower than the average correlation among the country market indices, 0.70. On the other hand, the average correlation among style local portfolios is relatively high at 0.66. The correlation matrix also indicates that the U.S. market index is substantially less correlated with each foreign country local portfolio than with the matching country market index; for instance, the correlation of the U.S. market index is 0.59 (0.82) with the Canadian local portfolio (market index), 0.28 (0.82) with the German local portfolio (market index), 0.27 (0.51) with the Japanese local portfolio (market index), and 0.48 (0.84) with the U.K. local portfolio (market index). The U.S. market index also has relatively low correlations with some of the industry local portfolios; for instance, the correlation is 0.46 with the energy local portfolio, 0.42 with the consumer staples local portfolio, 0.49 with the health care local portfolio, and 0.26 with the utilities local portfolio.

The key parameter values presented in Table 28 strongly suggest that investors should be able to benefit in terms of the enhanced mean-variance efficiency by including the local portfolios in their overall portfolio holdings. We formally test this proposition in the following subsection.

3.5.2 Mean-variance optimization with local portfolios

In this subsection, we formally test if investors can benefit in terms of mean-variance efficiency from holding international local portfolios. In doing so, we assume that investors would like to consider local portfolios to augment the stock market indices of our sample of nine developed countries. Thus, focus is on deciding if local portfolios may allow investors to further span the mean-variance space beyond whats feasible with country stock market indices. As inputs for solving for the optimal portfolios, we utilize the mean, standard deviation, and correlations of the returns from country market indices and local portfolios provided in Table 28. It is recalled that these parameters are computed over the period of January 1995–December 2014.

Specifically, we use the F-test proposed by [82] to test the significance of the mean-variance gains from adding the "test assets" of local portfolios to the "benchmark assets" of stock market indices. If short sales are allowed, the F-tests can be implemented in terms of the maximal Sharpe ratios, θ_1 and θ_2 attainable in the set of N_1 and N_2 assets, respectively, where N_1 is the number of base assets, and $N_2(\geq N_1)$ is the number of total assets (base assets plus test assets). The test statistic can be written as follows:

$$F = \frac{T - N_2}{N} \frac{\hat{\theta}_2^2 - \hat{\theta}_1^2}{1 + \hat{\theta}_1^2}, \tag{15}$$

where T is the number of time series observations, and $N = N_2 - N_1$. The F-test corresponds to the joint hypothesis of zero intercepts in a system of multivariate regression of the additional N asset returns on the original N_1 asset returns, and the test statistic has an F-distribution with $(T - N_2; N)$ degrees of freedom. However, if short sales are not allowed, the test statistic above does not follow any conventional distribution. Hence, in approximating the unknown distribution with simulation, we follow the procedure proposed by [86].[18] For simplicity, we call both (with and without short sales) tests as GRS tests.

As a first step of our analysis, we solve for the optimal international portfolio comprising nine country stock market indices and test if investors may significantly benefit from holding the resulting optimal portfolio as opposed to just holding the U.S. stock market index. As can be seen from Panel A of Table 29, the optimal portfolio returns have the mean of 2.31% (1.01%), standard deviation of 8.74% (4.82%), and a Sharpe ratio of 0.236 (0.159) if short sales are (not) allowed. Recall that U.S. market index has a Sharpe ratio of 0.152 from Panel A of Table 28. GRS test results indicate that the mean-variance gains from holding the optimal international portfolio comprising stock market indices are statistically insignificant, whether short sales are allowed or not, which is consistent with the previous findings in the literature. This result motivates considering local portfolios as a way of augmenting stock market indices.

Panel B of Table 29 shows that when investors choice set is augmented with the nine country local portfolios, the augmented optimal portfolio has a Sharpe ratio

[18] We implement the simulation process as following: First, (i) the betas and the associated residual covariance matrix of test assets on the benchmark assets and (ii) the first two moments of benchmark asset returns are derived from the historical data. Assuming that the alphas of test assets against the benchmark assets are all zeros, random samples of joint returns over T time periods are drawn from a multivariate standard normal distribution with the estimated parameters. From these simulated returns, we compute the maximum Sharpe ratios of $\hat{\theta}_2^2$ and $\hat{\theta}_1^2$ and the value of the test-statistic, $\frac{T-N_2}{N}\frac{\hat{\theta}_2^2-\hat{\theta}_1^2}{1+\hat{\theta}_1^2}$, is recorded. The empirical distribution of the test-statistic under the null is approximated by repeating this process 2,000 times.

Table 29: Mean-Variance Optimization with Local Portfolios

	Panel A		Panel B		Panel C		Panel D		Panel E	
Benchmark Assets	U.S. Mkt Index		Country Indices		Country Indices		Country Indices		Country Indices	
Test Assets	8 Other Mkts		Country Locals		Industry Locals		Style Locals		All Three Locals	
	Short Sales		Short Sales		Short Sales		Short Sales		Short Sales	
	With	Without	With	Without	With	Without	With	Without	With	Without
Country Indices										
Australia	0.463	0.000	0.350	0.000	0.192	0.000	0.208	0.000	0.250	0.000
Canada	0.868	0.310	-0.226	0.000	0.260	0.000	0.036	0.000	-0.049	0.000
France	0.591	0.000	0.060	0.000	0.192	0.000	0.216	0.000	0.160	0.000
Germany	-1.107	0.000	-0.433	0.000	-0.437	0.000	-0.311	0.000	-0.360	0.000
Hong Kong	0.070	0.000	0.150	0.000	-0.072	0.000	0.152	0.000	0.030	0.000
Japan	-1.097	0.000	-1.083	0.000	-0.426	0.000	-0.426	0.000	-0.189	0.000
Switzerland	1.446	0.413	0.193	0.000	0.401	0.000	-0.032	0.000	-0.213	0.000
U.K.	-1.513	0.000	-0.726	0.000	-0.791	0.000	-1.018	0.000	-0.687	0.000
U.S.	1.279	0.277	0.526	0.000	0.275	0.000	0.328	0.000	0.167	0.000
Country Locals										
Australia			-0.206	0.000					0.117	0.000
Canada			0.548	0.397					0.333	0.148
France			0.432	0.009					0.420	0.000
Germany			-0.447	0.000					-0.321	0.000
Hong Kong			-0.036	0.000					0.155	0.000
Japan			0.770	0.000					0.082	0.000
Switzerland			0.577	0.252					0.479	0.000
U.K.			-0.050	0.000					-0.163	0.000
U.S.			0.603	0.342					-0.208	0.000
Industry Locals										
Energy					-0.067	0.000			-0.320	0.000
Materials					-0.250	0.000			-0.351	0.000
Industrials					-0.435	0.000			-0.719	0.000
Cons. Disc.					0.056	0.000			0.018	0.000
Cons. Stap.					0.360	0.152			0.138	0.075
Health Care					0.338	0.264			0.299	0.217
Financials					0.708	0.149			0.301	0.020
Information Technology					0.308	0.120			0.437	0.093
Telecom Serv.					-0.017	0.000			0.028	0.000
Utilities					0.405	0.315			0.201	0.297
Style Locals										
Small Growth							-0.440	0.000	-0.571	0.000
Small Core							-0.153	0.000	-0.264	0.000
Small Value							0.211	0.000	0.109	0.000
Middle Growth							-0.306	0.000	-0.712	0.000
Middle Core							0.206	0.000	0.475	0.000
Middle Value							0.792	0.406	0.982	0.000
Large Growth							0.145	0.000	-0.364	0.000
Large Core							1.183	0.522	1.048	0.150
Large Value							0.210	0.072	0.262	0.000
Optimal portfolio returns										
Mean (%/month)	2.305	1.009	2.705	1.473	2.401	1.356	2.553	1.220	4.201	1.434
Std(%/month)	8.744	4.823	6.475	4.978	4.819	3.786	5.027	3.763	5.476	3.939
Sharpe ratio	0.236	0.159	0.381	0.247	0.448	0.294	0.460	0.260	0.723	0.303
GRS tests										
Test-statistic	0.978	0.116	2.092	0.900	3.052	1.381	3.655	1.063	3.348	0.490
p-value	0.454	0.750	0.031	0.000	0.001	0.000	0.000	0.000	0.000	0.000

of 0.381 (0.247) if short sales are (not) allowed. GRS tests indicate that the mean-variance gains from augmented international diversification relative to the benchmark case are statistically significant at the 5% (1%) level when short sales are (not) allowed. If short sales are not allowed, the augmented optimal portfolio is comprised of Canada local (39.7%), Switzerland local (25.2%), and the U.S. local (34.2%); country market indices optimally receive zero weights.

When investors simultaneously optimize their portfolio holdings across nine country market indices and ten industry local portfolios, the Sharpe ratio of the augmented optimal portfolio becomes even higher, i.e., 0.448 (0.294) when short sales are (not) allowed. As can be seen from Panel C of Table 29, GRS tests indicate that the gains from augmented diversification is significant at the 1% level, regardless of whether short sales are allowed. It is also noted that when short sales are not allowed, the augmented optimal portfolio is comprised of local portfolios of consumer staples (15.2%), health care (26.4%), finance (14.9%), information technology (12.0%), and utilities (31.5%); it is noted that the composition of the augmented optimal portfolio is strongly tilted toward less- or non-tradable industries like utilities, health care, and consumer staples. Again, country market indices receive zero weights when short sales are not allowed; when short sales are allowed, however, five country indices (Australia, Canada, France, Switzerland, and U.S.) receive positive weights while the remaining four country indices receive negative weights.

When investors augment the nine country market indices with nine style local portfolios and optimize their portfolio selection, the Sharpe ratio becomes higher than that of the benchmark case, i.e., 0.460 (0.260) when short sales are (not) allowed. As shown in Panel D of Table 29, the gains from augmented optimization are statistically significant at the 1% level, whether or not short sales are allowed. When short sales are not allowed, the augmented optimal portfolio is comprised of middle-value local (40.6%), large-core local (52.2%), and large-value local (7.2%). Clearly, value-oriented portfolios are given substantial weights, with no weights allocated to growth oriented portfolios. Unexpectedly, when short sales are not allowed, no small-cap oriented portfolios are given any positive weights despite their low R^2s, due to quite low mean returns for small-growth and small-core portfolios, as shown in Panel D of Table 28.

It is noted that small-value portfolio receives a positive weight when short sales are allowed, while small-growth and small-core portfolios receive negative weights in the optimal portfolio. Remarkably, country market indices receive no positive weights at all in Panel B-D if short sales are not allowed. This observation suggests that during our sample period, country market indices could have contributed to the mean-variance efficiency only when short sales are allowed.

Panel E of Table 29 provides the results from simultaneous portfolio optimization across nine country market indices and three sets of local portfolios, i.e., 9 country local portfolios, 10 industry local portfolios, and 9 style local portfolios. The augmented optimal portfolio has a Sharpe ratio of 0.723 (0.303) when short sales are (not) allowed, which is much higher than the Sharpe ratio of any of the three augmented optimal portfolios discussed in Panels B-D of Table 29. When short sales are not allowed, country market indices receive zero weights and positive weights are concentrated in industry local portfolios such as consumer staples (7.5%), health care (21.7%), information technology (9.3%), and utilities (29.7%). Apart from these industry local portfolios, Canada local and big-core local portfolios receive 14.8% and 15.0% weights, respectively. The increase in the Sharpe ratio relative to the benchmark case is significant at the 1% level, with or without short sales. Our findings here suggest that the three types of local portfolios complement each other to span the mean-variance space.

Figure 9 illustrates the effects of adding local portfolios on enhancing the mean-variance efficiency. Adding country local portfolios to the portfolio consisting of country market indices expands investment opportunity significantly. Adding all

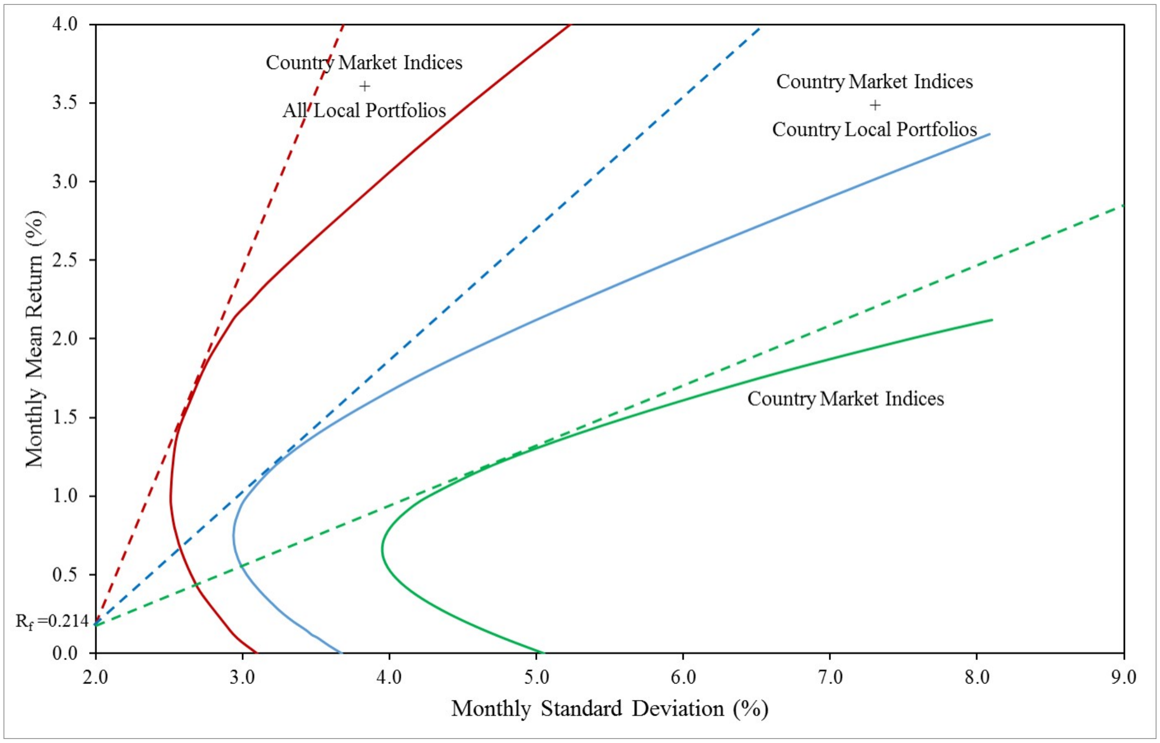


Figure 9: Efficient Frontiers of International Portfolios: The Effects of Local Portfolios

This figure plots the efficient frontier of portfolios comprising the nine country market indices (green solid line), and that of portfolios comprising country market indices and country local portfolios (blue solid line), and that of a portfolio comprising country market indices and three sets of local portfolios (red solid line). The dotted lines represent the capital market lines with the risk-free asset for each of the three portfolios. The risk-free rate is proxied by the average of the one-year U.S. Treasury yields during the period 1995-2014.

three types of local portfolios increases the mean-variance efficiency much further. Overall, our findings presented in Table 29 and Figure 9 send a clear message that investors can significantly benefit from augmented international diversification with country market indices and local portfolios of our sample of developed markets.

Table 30 further examines the robustness of our findings in portfolio analysis in two subsample periods: 1995-2004 and 2005-2014. Panel A shows that in both subsamples the nine country market indices can be spanned by the U.S. market index. In particular, it shows that the Sharpe ratio of the optimal portfolio consisting of nine

Table 30: Mean-Variance Optimization with Local Portfolios: Subsample Analysis

This table reports the optimal weight of portfolios comprising country market indices and local portfolios, the summary statistics of the optimal portfolio returns, and GRS test results with and without short sales for two subsample periods, 1995-2004 and 2005-2014. In Panel A, the benchmark asset is the U.S. market index and the test assets are country market indices of the eight other countries. Across Panels B, C, D, and E, we use the nine country market indices as the benchmark assets. We use country local, industry local, and style local portfolios as the test assets for Panels B, C, and D, respectively. In Panel E, we consider all of 28 local portfolios as the test assets. Mean and standard deviation (Std) are estimated from monthly optimal portfolio returns over the corresponding sub-sample periods. Sharpe ratios are computed with the risk-free rate proxied by the one year U.S. Treasury yield. The test-statistic and the associated p-value at the bottom of each panel provide the results of testing the null hypothesis that the maximum Sharpe ratio attainable with the augmented assets is the same as that attainable with the benchmark assets.

	Panel A		**Panel B**		**Panel C**		**Panel D**		**Panel E**	
Benchmark Assets	U.S. Mkt Index		Country Indices		Country Indices		Country Indices		Country Indices	
Test Assets	8 Other Mkts		Country Locals		Industry Locals		Style Locals		All Three Locals	
	Short Sales		Short Sales		Short Sales		Short Sales		Short Sales	
	With	Without	With	Without	With	Without	With	Without	With	Without
First subsample: 1995-2004										
Optimal portfolio returns										
Mean (%/month)	2.862	1.233	3.815	2.044	2.998	1.521	3.184	1.615	6.144	1.878
Std (%/month)	7.624	4.698	6.188	4.472	4.407	3.338	5.297	3.884	5.147	3.717
Sharpe ratio	0.328	0.186	0.558	0.377	0.599	0.348	0.533	0.323	1.124	0.409
GRS tests										
Test-statistic	1.109	0.113	2.105	1.283	2.305	0.920	1.821	0.835	3.118	0.414
p-value	0.362	0.600	0.036	0.000	0.017	0.003	0.073	0.003	0.000	0.000
Second subsample: 2005-2014										
Optimal portfolio returns										
Mean (%/month)	1.755	0.946	3.469	1.139	3.166	1.619	2.563	1.107	4.026	1.527
Std (%/month)	6.795	5.139	8.105	4.579	5.526	4.322	4.068	3.831	4.593	3.988
Sharpe ratio	0.240	0.160	0.413	0.222	0.551	0.346	0.600	0.257	0.850	0.352
GRS tests										
Test-statistic	0.557	0.117	1.217	0.284	2.364	1.013	3.263	0.486	1.878	0.310
p-value	0.810	0.643	0.293	0.128	0.015	0.003	0.002	0.018	0.015	0.005

country market indices is lower in the more recent period than that in the earlier subsample period. This finding is consistent with the view that country market indices have become more integrated over time, thus reducing the diversification benefits across country market indices. Panel B shows that adding country local portfolios to the benchmark portfolio consisting of nine country market indices provides significant gains only in the early subsample period. Panels C, D, and E of Table 30 confirm our finding in Table 29 that the local portfolios organized along industry and style dimensions are very effective in further spanning the mean-variance space and generate extra gains relative to the benchmark portfolio.

In this section, we systematically identify local stocks and construct local portfolios based on the granular, bottom-up analysis of heterogeneous integration across individual firms. We then show that the local portfolios, comprised of stocks least driven by the common global factors, allow investors to span the mean-variance space much beyond whats feasible with stock market indices. Thus, inferences of the gains from international diversification solely from stock market indices, the usual practice among practitioners and academics, are likely to very much understate the true magnitude of benefits that world stock markets can provide. At the macro level, local stocks can play an important role of countervailing against the rising, pervasive effect of the common global factors on the asset prices that accompanies financial integration. This may keep global risk sharing effective and also help to keep the cost of capital from rising around the world.[19]

3.6 Robustness Checks

In this section, we conduct robustness checks of the previous findings, focusing on the effets of (i) using alternative proxies for the global factors and (ii) measuring investment returns in alternative base currencies, apart from the U.S. dollar.

3.6.1 Alternative proxies for the global factors

Our previous analysis of the gains from augmented international diversification is based on using the local portfolios constructed from the 'principal components' as proxies for the global factors. Since there are alternative proxies we can use for the global factors, it would be important to check the robustness of the previous portfolio results to using alternative proxies for the global factors. To that end, we replicate

[19] As in most previous studies, we also implicitly assume here that investors bear the currency risk, rather than hedge against the risk. As shown by the existing studies, e.g., [70], if investors judiciously hedge the currency risk, the gains from international diversification may be further enhanced.

our portfolio analysis using the global versions of [72] three factors, [28] four factors, and [73] five factors obtained from French database to proxy for the global factors, in lieu of the principal components extracted from various stock indices.

Specifically, we first convert daily global factors to weekly factors and then regress weekly stock returns on Fama-French three factors, Carhart four factors, or Fama-French five factors to estimate R^2s for individual firms. The R^2s thus computed, not shown here for brevity, are widely distributed, albeit somewhat less widely than those shown in Figure 1, still confirming the strong heterogeneity of global integration at the firm-level. Similar to Figure 1, the distributions of R^2s shift to the right in more recent years, reflecting a greater degree of global integration among our sample firms. Using the bottom deciles of stocks sorted on the R^2s, we construct three sets of local portfolios representing country, industry, and style dimensions, based on each of the three sets of alternative proxies for the global factors metioned above.

As was done previously, we solve for the augmented optimal portfolio alternatively using each set of local portfolios, together with the nine stock market indices. We then test the null hypothesis that the maximal Sharpe ratio attainable with the augmented local portfolios is the same as that attainable with the benchmark assets of nine country market indices. Results are reported in Table 31. Specifically, Table 31 provides the mean, standard deviation, and the Sharpe ratio of each of the three augmented optimal international portfolios, with and without short sales. In addition, the last two rows of the table report GRS test statistics and the associated p-values.

A few things are noteworthy in Table 31. First, as indicated by p-values, the increase in the Sharpe ratio due to the augmented diversification is statistically significant at the conventional levels in every case, regardless of which alternative proxies are used for the global factors. Thus, our portfolio results presented in Table 29 are robust to the use of alternative proxies for the global factors. The Sharpe ratio, however, tends to be highest for Fama-French five factors followed by Carhart four factors

Table 31: Mean-Variance Optimization with Local Portfolios Constructed from the Alternative Global Factors

This table reports the optimal portfolios comprising country market indices and local portfolios constructed from Fama-French three global factors, Carhart four global factors, and Fama-French five global factors, with and without short sales. We first convert these daily global factors to weekly factors and then regress individual firm weekly returns in year t on Fama-French or Carhart factors and estimate individual firm's R^2. Then we select firms with lowest 10% R-squares in each country, industry, and style dimension and form Fama-French, or Carhart Local Portfolios and calculate value-weighted monthly portfolio returns. The performance measures of the optimal portfolios comprising country market indices and local portfolios constructed by each of three sets of alternative factors are reported in this table. Mean and standard deviation (Std) are estimated from monthly returns of optimal portfolio that has maximum Sharpe ratio over the sample period from 1995:01 to 2014:12. Sharpe ratios are computed with the risk-free rate proxied by one year U.S. T-bill rate. The F-statistic and p-value at the bottom of each panel provide results of testing the null hypothesis that the maximum Sharpe ratio attainable with the augmented assets is the same as that attainable with the benchmark assets.

	Panel A		Panel B		Panel C		Panel D	
Benchmark Assets	Country Indices		Country Indices		Country Indices		Country Indices	
Test Assets	Country Locals		Industry Locals		Style Locals		All Three Locals	
	Short Sales		Short Sales		Short Sales		Short Sales	
	With	Without	With	Without	With	Without	With	Without
Fama-French 3 factors								
Optimal portfolio returns								
Mean (%/month)	2.260	1.137	1.932	1.050	2.271	1.092	2.759	1.066
Std (%/month)	5.534	3.949	4.445	3.197	5.428	3.737	4.703	3.050
Sharpe ratio	0.365	0.227	0.380	0.253	0.374	0.228	0.536	0.270
GRS tests								
Test-statistic	1.817	0.656	1.872	0.868	1.974	0.664	1.594	0.353
p-value	0.066	0.013	0.050	0.005	0.043	0.005	0.036	0.003
Carhart 4 factors								
Optimal portfolio returns								
Mean (%/month)	3.340	1.274	2.486	1.264	2.263	1.165	3.702	1.293
Std (%/month)	7.902	4.182	5.104	3.809	5.049	3.660	5.691	3.557
Sharpe ratio	0.392	0.247	0.440	0.268	0.400	0.252	0.608	0.296
GRS tests								
Test-statistic	2.302	0.895	2.898	1.051	2.456	0.964	2.166	0.459
p-value	0.017	0.005	0.002	0.002	0.011	0.000	0.001	0.000
Fama-French 5 factors								
Optimal portfolio returns								
Mean (%/month)	3.059	1.219	2.710	1.374	2.518	1.244	3.533	1.404
Std (%/month)	7.309	4.157	5.389	3.735	5.161	3.769	5.193	3.572
Sharpe ratio	0.385	0.235	0.458	0.303	0.441	0.266	0.634	0.326
GRS tests								
Test-statistic	2.180	0.754	3.240	1.500	3.260	1.143	2.386	0.595
p-value	0.024	0.011	0.001	0.000	0.001	0.001	0.000	0.000

and Fama-French three factors. Consider, for instance, the case where investors optimally augment their portfolios using all three types of local portfolios (i.e, country, industry, and style.). As can be seen in Panel D of Table 31, the resulting optimal portfolio has a Sharpe ratio of 0.634 (0.326) when short sales are (not) allowed if Fama-French five factors are used to proxy the global factors. If Carhart four factors are used as the proxies, the Sharpe ratio would be 0.608 (0.296), while the Sharpe ratio would be 0.536 (0.270) when Fama-French three factors are used as the proxies. In comparison, the Sharpe ratio is 0.723 (0.303), as shown in Panel E of Table 29, if the principal components (PCs) are used to proxy the global factors. Comparison of the results presented in Tables 29 and 31 indicates that the Sharpe ratios from Fama-French five factors and the PCs used in our main analysis are largely comparable. As a practical matter, investors thus may use Fama-French five factors, as well as the PCs, for the purpose of identifying local stocks and optimally holding them.

It is recalled that to proxy the global factors, we previously extracted the principal components (PCs) from the country market indices, industry indices, and style indices 'separately'. To check the robustness of our results to an alternative way of extracting PCs, we first form a pool of 28 indices, comprising nine country, ten industry, and nine style indices, and extract PCs from the pooled indices. In particular, we extract the first six PCs which can explain at least 90% of the total volatility in the covariance matrix of the 28 indices and replicate the portfolio analysis as in Table 29. Our un-tabulated results indicate that the empirical findings reported in Table 29 are robust to the use of these alternative PCs extracted from the pooled approach as proxies for the global factors. In other words, the increases in the Sharpe ratios of the optimal international portfolios augmented with the local portfolios remain statistically significant when the pooling approach is used. More often than not, however, the Sharpe ratios tend to be somewhat lower than those reported in Table 29, implying that it may be advantageous to extract PCs separately, thereby ensuring to capture information from each of the three dimensions.

3.6.2 Alternative base currencies

In our previous analysis, we employed stock and index returns measured in U.S. dollars, possibly raising the concern that our key findings reported in Table 29 may not necessarily hold for international investors who would measure investment returns in different currencies. To address this legitimate concern, we replicate our portfolio analysis using each of the eight currencies matching our sample countries as the alternative base currency. The results, provided in Table 32, show that our findings reported in Table 29 remain robust, to a large extent, to the use of different base currencies.[20] Specifically, our GRS test results indicate that the increase in the Sharpe ratio due to the augmented diversification with the local portfolios is always statistically significant at the conventional significance levels, with and without short sales, for those investors who use the Australian dollar, Canadian dollar, Hong Kong dollar, Japanese yen, Swiss franc, or the U.K. pound as their base currencies.

As can be seen in Table 32, the results are a little different for the French and German investors who share the common European currency, the euro, during much of our sample period. For the French investors, the increase in the Sharpe ratio is insignificant when they diversify using either country or style local portfolios when short sales are not allowed. Also, the increase in the Sharpe ratio is insignificant when the French investors use industry local portfolios for diversification when short sales are allowed. For the German investors, the Sharpe ratio increase is insignificant when they diversify using industry local portfolios when short sales are allowed or using style local portfolios when short sales are not allowed. The portfolio performance results are not identical for the French and German investors because in the

[20]To be consistent with the use of alternative base currencies, we use proxies for the local risk-free rates in our portfolio analysis here. The local risk-free rate proxy we use is 1-year deposit rate for Australia, Germany, Hong Kong, and Switzerland, 1-year T-bill rate for Canada and France, 1-year discount rate for Japan, and 3-month T-bill rate for the U.K.

Table 32: Mean-Variance Optimization with the Alternative Base Currencies

This table reports the summary statistics of the optimal portfolio returns based on currencies of our eight other sample countries (i.e., Australia, Canada, France, Germany, Hong Kong, Japan, Switzerland, and the U.K.), and GRS test results with and without short sales. The benchmark assets are the nine country market indices. For Panels A, B, and C, we use country local, industry local, and style local portfolios as the test assets, respectively. In Panel D, we consider all of 28 local portfolios as the test assets. Mean and standard deviation (Std) are estimated from monthly optimal portfolio returns from 1995:01 to 2014:12. Sharpe ratios are computed with the risk-free rate proxied by the one year U.S. Treasury yield. The test-statistic and the associated p-value at the bottom provide the results of testing the null hypothesis that the maximum Sharpe ratio attainable with the augmented assets is the same as that attainable with the benchmark assets.

		Panel A		**Panel B**		**Panel C**		**Panel D**	
Benchmark Assets		Country Mkt Indices		Country Mkt Indices		Country Mkt Indices		Country Mkt Indices	
New Assets		Country Locals		Industry Locals		Style Locals		All Three Locals	
		Short Sales		Short Sales		Short Sales		Short Sales	
		With	Without	With	Without	With	Without	With	Without
Australia									
Optimal portfolio returns	Mean (%/month)	2.436	1.225	3.687	1.518	3.792	1.194	7.001	1.550
	Std (%/month)	5.732	3.437	7.279	3.866	8.531	3.525	10.616	3.788
	Sharpe ratio	0.343	0.220	0.442	0.271	0.389	0.206	0.615	0.285
GRS tests	Test-statistic	1.681	0.903	3.153	1.383	2.486	0.748	2.308	0.512
	p-value	0.095	0.000	0.001	0.000	0.010	0.000	0.000	0.000
Canada									
Optimal portfolio returns	Mean (%/month)	2.813	1.189	3.230	1.557	2.006	1.115	5.543	1.445
	Std (%/month)	6.942	3.465	7.106	4.344	4.674	3.189	7.535	3.445
	Sharpe ratio	0.363	0.259	0.413	0.291	0.367	0.258	0.697	0.335
GRS tests	Test-statistic	1.853	1.129	2.483	1.414	1.914	1.120	2.990	0.664
	p-value	0.060	0.000	0.008	0.000	0.051	0.000	0.000	0.000
France									
Optimal portfolio returns	Mean (%/month)	3.013	1.555	3.637	1.805	4.032	1.214	5.691	1.944
	Std (%/month)	7.785	6.543	9.414	6.601	10.369	5.330	9.253	6.995
	Sharpe ratio	0.357	0.199	0.360	0.236	0.365	0.181	0.588	0.242
GRS tests	Test-statistic	1.686	0.372	1.560	0.688	1.826	0.195	2.004	0.249
	p-value	0.094	0.162	0.120	0.018	0.065	0.214	0.003	0.031
Germany									
Optimal portfolio returns	Mean (%/month)	3.292	1.625	3.579	1.742	3.898	1.207	4.606	1.910
	Std (%/month)	8.295	6.757	9.423	6.456	10.113	5.290	7.525	6.938
	Sharpe ratio	0.368	0.201	0.352	0.229	0.359	0.178	0.575	0.237
GRS tests	Test-statistic	1.895	0.416	1.458	0.639	1.753	0.194	1.911	0.239
	p-value	0.054	0.094	0.157	0.023	0.079	0.185	0.006	0.040
Hong Kong									
Optimal portfolio returns	Mean (%/month)	4.048	1.389	2.649	1.274	2.517	1.137	4.754	1.312
	Std (%/month)	9.765	4.353	5.249	3.565	5.833	3.767	7.124	3.659
	Sharpe ratio	0.381	0.244	0.443	0.266	0.376	0.215	0.622	0.270
GRS tests	Test-statistic	2.211	0.997	3.050	1.144	2.113	0.664	2.319	0.390
	p-value	0.022	0.001	0.001	0.001	0.029	0.003	0.000	0.000
Japan									
Optimal portfolio returns	Mean (%/month)	2.450	1.533	3.269	1.541	2.273	1.234	4.758	1.592
	Std (%/month)	6.249	5.343	6.682	4.679	5.627	4.308	7.717	4.782
	Sharpe ratio	0.386	0.279	0.483	0.321	0.397	0.277	0.611	0.325
GRS tests	Test-statistic	1.844	0.920	3.413	1.373	2.045	0.890	2.074	0.469
	p-value	0.062	0.018	0.000	0.000	0.036	0.014	0.002	0.001
Switzerland									
Optimal portfolio returns	Mean (%/month)	2.250	1.047	2.602	1.209	2.161	1.082	3.149	1.156
	Std (%/month)	5.700	3.773	5.869	4.002	5.301	3.728	5.451	3.661
	Sharpe ratio	0.369	0.239	0.419	0.266	0.380	0.251	0.551	0.276
GRS tests	Test-statistic	1.746	0.618	2.378	0.855	1.938	0.768	1.659	0.322
	p-value	0.080	0.016	0.011	0.003	0.048	0.001	0.025	0.006
U.K.									
Optimal portfolio returns	Mean (%/month)	4.332	1.320	2.602	1.289	2.542	1.140	4.927	1.311
	Std (%/month)	11.076	4.409	5.150	3.541	5.809	3.679	7.282	3.601
	Sharpe ratio	0.360	0.222	0.439	0.268	0.379	0.217	0.630	0.270
GRS tests	Test-statistic	1.860	0.758	2.994	1.185	2.185	0.704	2.395	0.396
	p-value	0.059	0.006	0.001	0.000	0.024	0.001	0.000	0.000

early years of our sample period, i.e., 1995-1998, the two countries still had their separate national currencies; furthermore, they faced different local interest rates. It is, however, noteworthy from Panel D of Table 32 that when investors diversify using all three types of local portfolios, the resulting increase in the Sharpe ratio is always statistically significant for all eight alternative base currencies (as well as for the U.S. dollar) at the 5% level or better, with or without short sales.

The above results from our robustness checks indicate that the case for international portfolio diversification with local stocks is very strong and robust.

3.7 Concluding Remarks

Since the 1980s, developed stock markets have been integrating in earnest, allowing investors to diversify their portfolios internationally and reap benefits from the enhanced risk-return efficiency of their portfolios. Most likely, however, the same global integration of these markets eventually led to much higher correlations between these markets, making it difficult for investors to continue to benefit from international portfolio diversification. To the extent that this is true, global integration of financial markets, which was once hailed as a new source of welfare gains, can turn out to be at least partly self-defeating its own rationale in the long run. This concern about the virtue of international diversification is shared by academics as well as practitioners, as succinctly expressed by [160]'s article published in Financial Analyst Journal titled, "Where are the gains from international diversification?" Against this backdrop, we proposed in this paper a new way to capture significant gains from international diversification.

Underlying our new diversification strategy is the recognition that the degree of global integration varies a great deal at the firm level. In other words, there exists a substantial number of individual stocks that are minimally integrated globally in each country, industry, and style categories. As a result, if investors systematically identify these local stocks that are least driven by common global factors and hold them optimally, they can still benefit significantly from international diversification as shown in this paper. In a nutshell, we proposed to take advantage of rich, granular variations in the degree of global integration at the firm level and conduct discreet and selective portfolio diversification with local stocks, limiting exposure to global factors.

Lastly, our analysis of firm-level integration also suggests that each stock market should be viewed as populated by individual stocks exhibiting continuous degrees of integration cross-sectionally, instead of comprising stocks that are either uniformly segmented or integrated or dichotomously distributed between local and global stocks within each sample country. Since asset pricing critically depends on whether and to what extent markets are integrated globally, the firm-level heterogeneity in integration documented in this paper may also have important implications for asset pricing. This and other related issues, however, are beyond scope of this paper.

APPENDIX A

COMPLEMENTARY MATERIALS

Table A1: Variable definitions

Dependent variables	Description	Data Source
Jumbo approval rate (count)	The fractions of approved jumbo loan applications to total jumbo loan applications across all lenders in county i and year t, where the fractions are based on approved jumbo loan counts	HMDA
Jumbo approval rate (volume)	The fractions of approved jumbo loan applications to total jumbo loan applications across all lenders in county i and year t, where the fractions are based on approved jumbo loan volumes	HMDA
Rate Spread	The price data take the form of a "rate spread". Lenders must report the spread (difference) between the annual percentage rate (APR) on a loan and the rate on Treasury securities of comparable maturity - but only for loans with spreads above designated thresholds. So rate spreads are reported for some, but not all, reported home loans.	HMDA
NPL/Family loans	1-4 family loans 90 or more days past due plus loans no longer accruing interest/total 1-4 family loans	Call Report
NPL/Family loans (first lien only)	NPL/family loans calculated only based on first liens	Call Report
Family charge-offs/Family loans	1-4 family loans charge-offs/ total 1-4 family loans	Call Report
Family charge-offs/Loan charge-offs	1-4 family loans charge-offs/ total loans charge-offs	Call Report
Borrower Controls		
Log(Applicant Income)	The average of the logarithm of applicant income reported in HMDA within county i of year t	HMDA
LTI Ratio	The average of the ratio of loan amount divided by reported applicant income within county i of year t	HMDA
Minority Fraction	The fraction of applicants who are minority over all applicants in county i of year t	HMDA
Female Fraction	The fraction of applicants who are female over all applicants in county i of year t	HMDA
Lender Controls		
Log(Assets)	The logarithm of bank total assets	Call Report
Leverage	The bank capital-asset ratio	Call Report
Accounting Profits	Net income to total assets	Call Report
Liquidity	Investment and traded securities to total assets	Call Report
Loans/Assets	Ratio of loans to total assets	Call Report
Deposits/Assets	Ratio of deposits to total assets	Call Report
Deposit Cost	Interest expenses on deposits to total deposits	Call Report
Letters of credit/Assets	Letters of credit in total assets	Call Report
Unused Loan Cmt/Assets	Unused loan commitments in total assets	Call Report
C&I Loans/Assets	Share of commercial and industrial loans to total assets	Call Report
Real Estate Loans/Assets	Share of real estate loans to total assets	Call Report
Securitization Ratio	The weighted average securitization ratio of banks in a given county (weighted by bank market shares), and for each bank the securitization ratio is computed as the total volume of securitized mortgages divided by the total volume of issued mortgages	HMDA
County Controls		
County Income Mean ('000)	County per capita income	BEA
County Income Growth (%)	County per capita income growth rate	BEA
HPI Growth (%)	The housing price index growth rate in year t	FHFA
HPI Growth Lag (%)	The housing price index growth rate in year $t-1$	FHFA

Table A2: Filters for Excluding Non-common Equity Securities

This table lists keywords for filtering out non-common equity securities in Datastream. If any keyword is detected in the corresponding variable, the associated security is excluded. Panel A lists identifiers for firm names (NAME). Panel B lists keywords for industry names (INDM) and codes (INDC6). Panel C lists country-specific identifiers.

Panel A. Non-common equity security codes

Non-common equity	Keywords
Debt	DEB DB DCB DEBT DEBENTURES DEBENTURE
Depository Receipts	ADR GDR
Duplicates	DUPLICATE DUPL DUP DUPE DULP DUPLI 1000DUPL XSQ XET
Expired securities	EXPIRED EXPD EXPIRY EXPY
Preferred Stock	PREFERRED PF PFD PREF PRF
Rights and Warrants	RIGHTS RTS WARRANT WARRANTS WTS WTS2 WARRT
Unit Trusts	UT IT RLST IT INVESTMENT TRUST INV TST UNIT UNT UNITS
Other Generic	500 BOND DEFER DEP DEPY ELKS ETF
Identifier Filters	FUND FD IDX INDEX LP MIPS MITS MITT MPS NIKKEI NOTE PERQS PINES PRTF PTNS PTSHP QUIBS QUIDS RATE RCPTS RECEIPTS REIT RETUR SCORE SPDR STRYPES TOPRS UNIT UNT UTS WTS XXXXX YIELD YLD

Panel B. Investment vehicle industry codes

Industry Name	Industry Code	Industry Name	Industry Code
AUTH. UNIT TRUSTS	UNITS	INVESTMENT COS. (UK)	INVCO
CURRENCY FUNDS	CURFD	INVESTMENT TRUST UK	IVTUK
EXCHANGE TRADED FUNDS	EXTRF	OFFSHORE FUNDS	OFFSH
INS.+PROPERTY FUNDS	INSPF	OPEN ENDED INV.COS.	OEINC
INV.TST INTERNATIONAL	ITINT	OTHER INV. TRUSTS	INVTO
INV.TST.EMERGING MKTS	ITEMG	REAL ESTATE	
INV.TST.GEOG.SPECLSTS	ITGSP	REAL ESTATE DEV.	RLDEV
INV.TST.VENTURE + DEV	ITVNT	SPLIT CAPITAL INV.TST	ITSPL
INVESTMENT COS. (6)	INVNK	VENTURE CAPITAL TRUST	ITVCT

Panel C. Country-specific identifiers

Country	Keywords
Australia	(Rights): RTS (Deferred): DEF DFD DEFF (Full and Partially Paid): PAID PRF
Canada	(Rights, Shares, Voting, subordinated voting): RTS SHS VTG SBVTG SUBD (Receipts are rights to receive stocks or options at a future date): RECPT Receipt (Exchangeable): EXH EXCHANGEABLE (Series): SR SER (Split Share Corporations a derivative of common stock): SPLIT
France	(certificates of investment or investment trusts): ADP CI CIP ORA ORCI OBSA OPCSM SGP SICAV FCP FCPR FCPE FCPI FCPIMT OPCVM
Germany	GENUSSCHEINE or GSH are securities, which are hybrid securities between a loan and equity: GENUSSCHEINE GSH
Switzerland	(the word USE and converted is always used with a Datastream code and the reference code always appears to be primary): USE CONVERTED CONV CONVERSION
United Kingdom	(ranking for dividend): ranking for dividend (book-keeping entry): PAID (Nonvoting): NV

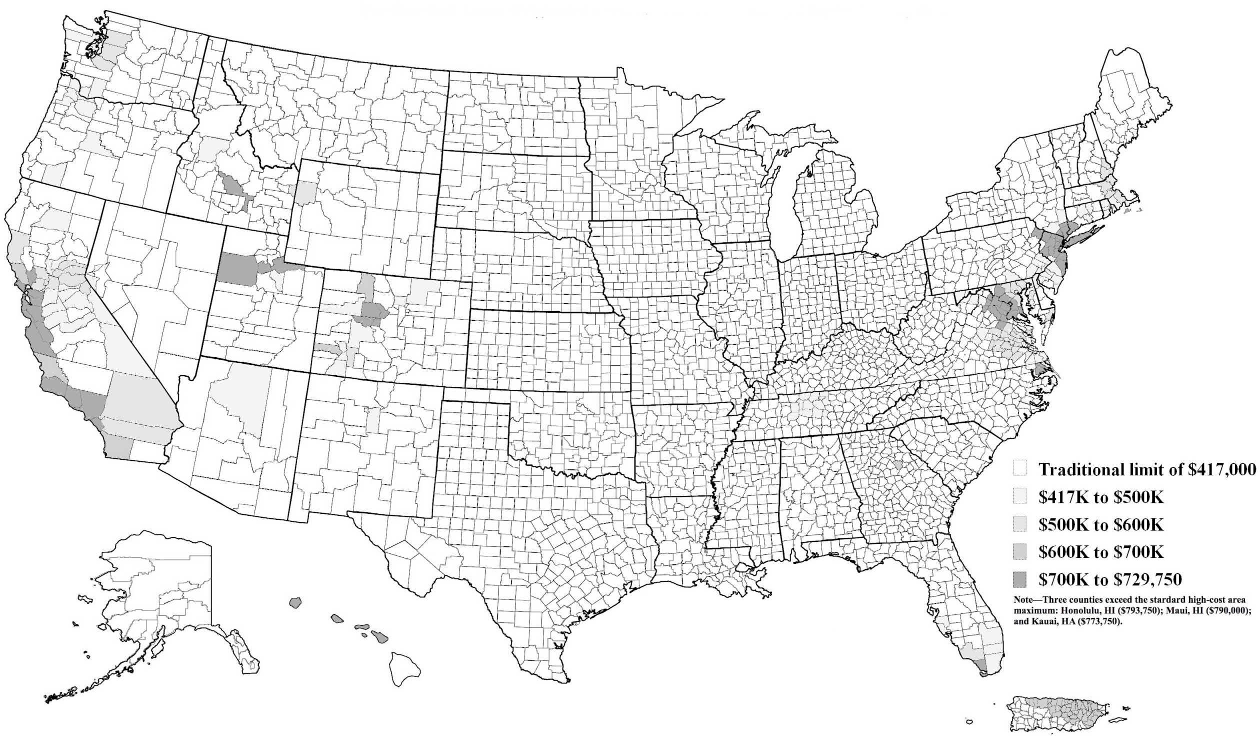


Figure A1: The map of the high-cost areas in 2008

This figure shows the map of the counties that are determined as the high-cost areas by the Federal Housing Finance Agency (FHFA). Counties that are marked in darker colors are determined as high-cost areas with higher conforming loan limits. The match between the color and the limit is listed on the right side of the figure.

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